ESSAYS ON LABOR MARKET TRANSITIONS AND WELFARE

by
Sung Ah Bahk

A dissertation submitted to Johns Hopkins University in conformity with the requirements for

the degree of Doctor of Philosophy

Baltimore, Maryland
August 2020

Abstract

Transition decisions in the labor market such as career, work, and human capital accumulation entail long term economic consequences, yet are difficult to make under the risk of skill-job mismatch. In this dissertation, I explore the choice mechanism for occupations and how this choice is related with the wealth and income of the decision maker.

In the first essay, I examine a channel between wealth and earnings inequality. Selecting into occupations that appropriately match their skills can lead to higher earnings levels for workers. Yet risk averse workers might be reluctant to experiment and to discover their highest earnings potential by moving between jobs because of the downside risk involved. I provide a model and empirical evidence of how workers learn about their skills by changing jobs that require different combinations of tasks. Using the estimated model, I find that the level of initial wealth has a large, long-term effect in income inequality over the life-cycle.

In the second essay, I report new evidence on why unemployment insurance (UI) benefits might lengthen job search durations. I examine whether unemployed individuals with higher levels of wealth search for different kinds of jobs, with different task levels, than those with lower levels of wealth. I find that an increase in UI benefit duration allows the unemployed to make larger changes in job-specific tasks relative to their pre-unemployment jobs.

In the third essay, co-authored with Kyungmin Kang, we ask whether the role of employer learning varies by worker task type. We build a model in which workers and firms learn about workers' multi-dimensional skills from productivity signals, where signal accuracy depends on a job's task intensity. We find that employer learning depends on the task intensity and the degree varies across educational groups.

Advisors:

Professor Robert Moffitt

Professor Yuya Takahashi

Professor Yingyao Hu

Acknowledgments

I am very grateful to my advisor and role model, Professor Robert Moffitt for his guidance and patience towards me throughout the years. I will always remember how generous he was for the time and effort he gave for his students, and I hope to serve my own students the same way. I would like thank Professor Yuya Takahashi for advising me since the very beginning of my research. Without his support, I would not have started and finished this work. I thank Professor Yingyao Hu for his constant presence and support, as he often filled me with encouragement when I needed it the most. I am lucky to have received immense help from many other Professors in the Department. I thank Professors Greg Duffee, Chris Carroll, Yujung Hwang, and Lixiong Li for their thoughtful comments. I also thank my undergraduate advisor Sung Hyun Kim for teaching me how fun economics research can be and for his continuing warm supports.

I thank my friend Kevin Yuan for everything we have done to pursue fun here at Hopkins, my 6 years of hard works for PhD felt short thanks to him. I also thank my classmates Edmund Crawly, Harold Chiang, Luigi Durand, Hanchen Jiang, and Osama Khan for times we enjoyed and struggled together. I also thank senior students, Kyungmin Kang, Shujaat Khan, Ding Xuan, and Andy Gray, and Yi Xin for helpful comments.

I would like to thank for warm Christian community that I met in Baltimore. Maryland Hope Church has been my second family and a place for me to reply on. I thank my family in Korea for unmeasurable support and love I owe. Lastly, I thank my best friend and partner David Rhim for always being by my side.

Contents

List of Tables

List of Figures

Chapter 1

Distributional Effects of Ability Learning and Career Choice

1.1 Introduction

Selecting the occupation that best matches one's personal skills allows for best job performance and is crucial not only for the individual but also for aggregate productivity within the larger economy. Workers who do not have perfect awareness of the true nature and level of their skills must learn, generally through the experience of moving between jobs and observing how their individual performance is compensated and by observing which types of jobs yield the highest earnings for them. However, risk-averse workers might be reluctant to experiment with job changes in order to identify the jobs that would compensate them most highly, and the inefficiencies resulting from this imperfect information might have greater impacts for workers with low wealth.

Although the idea of workers learning about their personal ability levels (hereafter simply “learning”) has been widely discussed in the literature since Jovanovic (1979), there has not been much empirical evidence regarding its importance or its existence. In this paper, I first provide the evidence for skill uncertainty and learning using reduced-form methods, and I then construct dynamic structural model that accounts for the benefits of learning in the labor market to analyze its implications for wealth and income inequality.

To show reduced-form evidence for learning in the labor market, I borrow Yamaguchi (2012)’s framework to define occupations according to the skill levels they require in two dimensions, “motor” and “cognitive”. This approach allows us to observe magnitudes or directions of occupational moves, including whether these moves represent a climb or a drop on task intensity scales, as well as whether a given job change is lateral (i.e., moving from a job that requires one type of skill into a job that requires a different type). Such a framework for examining occupational change makes it possible to evaluate such changes within a richer context than previous frameworks have. Previous frameworks have largely grouped occupations into distinct categories, thus flattening the level of detail available and only permitting binary observations regarding occupational transition (i.e., did the worker leave one particular occupation (yes/no) or enter another (yes/no)).

To identify the effect of learning, I assume that workers know the true relationship between skills and wages but do not know their own skill levels, and that the wage they receive on a job is equal to their true productivity in the job. They take a positive (negative) wage realization from a job with a high level of one type of task intensity to be a signal that they have high (low) skills for performing that task. If the worker views this signal as reflective of productivity, and if that worker makes future occupational choices based on it, we should observe a systematic difference in subsequent job choices between those who receive different signals from jobs of the same task intensity. Empirically, using panel data from the Longitudinal Survey of Youth 1979 (hereafter, NLSY79) on wages paid and data from the Dictionary of Occupational Titles on task intensities of different jobs, I estimate the "signal" the individual receives from wage residuals on jobs and then observe movements to different jobs with different intensities as a function of the signal received on a given job with a particular task intensity. I find that workers who receive a positive signal about their abilities tend to move up to jobs that use the same skills more intensively, whereas those who receive unexpectedly low wages are likely to adjust themselves to new occupations that require different sets of skills.

Based on this reduced-form finding, I then construct a structural career choice model to analyze the dynamic roles of learning and of initial assets in lifetime earnings. Workers receive new information about their skills from the wage signal in each period, and they make occupational choices to maximize their own expected lifetime utility, taking into account the benefit of learning. Wealth enters the model because people with low wealth are less likely to take risks due to the probability of sizable utility loss from taking suboptimal jobs under plausible assumptions such as constant relative risk aversion or credit constraints. While the model can allow for any finite dimensions for skills and tasks, I focus on just two dimensions: cognitive and motor skills.

The main difficulty in solving this dynamic optimization problem is the computational problem that arises because there are large numbers of state and choice variables for multiple periods of time. My solution algorithm builds on the Endogenous Grid Method proposed by Carroll (2006). I also use Broyden's method (Broyden (1965)), an extension to higher dimensions of the secant method of root finding, in order to avoid repeatedly evaluating the system of Jacobians, and save computation time by exploiting secant information instead.

The estimation results display a significant constant relative risk aversion coefficient, estimated using work history and wealth data from the NLSY79. I find that there are much larger payoffs for performing one unit of cognitive task compared to an equivalent unit of motor task. However, the penalty for overshooting a cognitive task – that is, of choosing a cognitive task that is too high for one's true ability – is much larger than it is for motor tasks. Also, the results show that workers start off with higher uncertainty in motor skills, but that uncertainty resolves faster than it does for cognitive skills over the life-cycle.

Using the model, I also simulate a proposal for Baby Bonds advanced by a current Presidential candidate, which is a federally seeded trust fund for every U.S. newborn. The simulation results imply that supporting young adults in the very beginning of their entry to the labor market will have a large and long-term effect on income inequality by, in effect, providing these workers with figurative "insurance" amidst their process of discovering their comparative advantages within the labor market. The model's results imply that this policy will be particularly beneficial for people with low initial wealth. Annual support of \$1,000 for 18 years will increase the income ratio between bottom 10% and top 10% of initial wealth group by 1.01 percentage points, and \$2,000 will increase it by 5.36 percentage points.

1.2 Relation to the Literature

This paper builds upon two strands of existing literature. The first is the literature on learning and labor market transitions. The idea of skill uncertainty and learning was first proposed in the classic matching model by Jovanovic in 1979. In his model, both workers and employers face uncertainty about workers' skills and it is only after they are matched and begin working is their true productivity revealed. They subsequently decide whether to remain matched or to split up. There has been other empirical work on learning and labor market transition although most of the learning literature has focused on workers' job-specific (Jovanovic (1979), Gorry et al. (2019)) or occupation-specific abilities (Kambourov and Manovskii (2009), Antonovics and Golan (2012), Papageorgiou (2014)). For example, the process of learning about skills within blue collar versus white collar jobs, or professional occupations versus non-professional occupations, has been widely studied. These studies found that nearly 20% of workers change their occupation every year, and that subsequent wage gains are as large as a third of early-career wage growth. (Kambourov and Manovskii (2009), Topel and Ward (1992)).

CHAPTER 1. DISTRIBUTIONAL EFFECTS OF ABILITY LEARNING AND CAREER CHOICE

A growing body of literature, since Autor et al. (2003), has considered task-specific approaches (Yamaguchi (2012), Sanders (2014), Autor and Dorn (2013)) instead of job or occupation-specific abilities using task information in DOT and its successor, the Occupational Information Network (O*NET). In this literature, skills are assumed to be task specific and to reflect the daily responsibilities of workers. For example, Yamaguchi (2012) and Sanders (2014) consider skills in two continuous dimensions, cognitive and motor. Compared to the job-specific or occupation-specific skills, the task-specific approach has many attractive characteristics for studying occupational mobility, because it allows comparisons among different occupations in terms of skill levels that are required to perform a job. In addition, it is easier to handle a large number of occupations when they are defined in task-specific skills.

Yamaguchi (2012) departs from Roy (1951), where workers choose occupations in which they have a comparative advantage. While many other Roy-type models (Heckman and Sedlacek (1985), Keane and Wolpin (1997), Lee and Wolpin (2006)) provide insights about issues in heterogeneous human capital in different occupational categories, Yamaguchi proposes a new interpretation for why skills in different occupations are rewarded differently and how they are transferable across occupations by assuming the returns to skills vary with task complexity. He assumes certainty about skills and and examines occupational mobility while workers accumulate skills at work (learning-by-doing). This paper builds upon Yamaguchi's extension of Roy model, and I introduce skill uncertainty and risk aversion to analyze the role of wealth in career choice and the resulting income inequality.

This paper also builds on a long literature that investigates the connection between wealth and risk-taking behavior represented by (Pratt (1978), Kimball (1989)). These two papers provide the theory of risk taking behavior. Pratt (1978) proposes the Arrow-Pratt measure of absolute risk aversion and derives necessary and sufficient conditions on utility functions for a decreasing risk premium with respect to wealth. Based on this theory, there have been a large number of empirical papers that examine relations between observed risk taking behaviors and wealth levels: for example, savings decisions and wealth under income uncertainty or allocations of savings to risky assets versus safe assets (Gourinchas and Parker (2002), Cagetti (2003))

There have been some studies that analyze occupational decisions as risky choices (King (1974), Saks and Shore (2005)). Most works in this vein focus on risk averse individuals' occupation choices, given some distributional characteristics pertaining to occupation, such as the mean or variance of wages within occupations and test whether workers with low wealth are likely to choose occupations that have low wage variances. Therefore they conclude that workers are likely to choose a certain occupation to another depending on their asset holdings. My paper is distinct from these works, in that it treats risk in career choice as deriving from workers' lack of knowledge of their own abilities, rather than from occupation-specific characteristics, and in that the uncertainty is gradually resolved from work experience.

To my best knowledge, this is the first paper to propose a learning channel between wealth and income inequality. I provide a dynamic model and empirical evidence to test this proposed channel and its implications for income inequality.

1.3 Data

Research on occupational mobility often struggles with the question of how best to group occupations into categories. Coarse definitions do not entirely capture the differences between and within occupations. There may exist a huge discrepancy among the occupations which are grouped in the same categories, and there may be some occupations in different categories but share similar characteristics in terms of the job tasks. However, finer distinctions (thus resulting in more categories) are hard to operationalize, because the number of parameters or states increase with the number of occupations. Therefore, many papers for occupation-specific human capital consider only a limited number of occupations up to Census one-digit occupations which categorize occupations into 12 subcategories (Johnson and Keane (2013), Papageorgiou (2014)).

In addition to these difficulties, it is also hard to evaluate on a practical level how similar or different two distinctly coded occupations are. Therefore, skill transfer across occupations is often ignored when assessing returns to occupational tenure. With traditional occupational groupings as distinct and flat categories, researchers only observe whether a worker has entered or exited a given category. Therefore, it is hard to analyze career movements apart from simply calculating transition probabilities.

To overcome this problem, I borrow Yamaguchi (2012)'s framework, which overcomes these challenges by defining occupation in a novel way. Using task information from the Dictionary of Occupational Titles (DOT), Yamaguchi defines an occupation as a bundle of tasks along two different dimensions, cognitive and motor complexity, while also accounting for each dimension's intensity. Therefore, occupations are represented as a simple 1 by 2 vector, where each number gives information about how difficult this job is to do in terms of the each skill dimension. For example, the average task complexity of professional occupations is (0.85, 0.45), while the average craftsman occupation is (0.52, 0.82). Occupations in professional categories on average require higher cognitive task compared to the average craftsman occupations, but motor task intensity is much larger for craftsman than professional occupations in average.

The advantage of using Yamaguchi's categorization is that it allows for richer evaluations of occupational mobility; not only can the frequency of movement be analyzed, but also the directionality of movement. For example, does the worker move up or down the scale of task complexity (along the cognitive and/or motor dimension), or does the worker perhaps move laterally - into a new job that requires different kinds of skills? Such a categorization method also allows me to observe how radical an occupational transition is, as we can examine the distance between the new and old task requirements.

The following subsections include explanations for the data constructed in Yamaguchi

(2012) and the additional variable, initial wealth in detail.

1.3.1 Dictionary of Occupational Titles

The Dictionary of Occupational Titles (DOT) contains detailed task information on 12,099 occupations. Each occupation is evaluated with respect to 62 characteristics, such as aptitudes, temperaments, necessary training time, physical demand, and working conditions. Yamaguchi (2012), like many other authors who use the DOT, categorizes these job characteristics into cognitive and motor tasks (Bacolod and Blum (2010), Ingram and Neumann (2006)). Autor et al. (2003) and Autor and Dorn (2013) consider three skill dimensions including abstract, manual, and routine task to analyze the allocation of task between labor and capital due to the technological changes in the labor market.

The DOT variables that Yamaguchi uses to measure cognitive complexity consist of two worker function variables (data and people), three general educational development variables (reasoning, mathematical, and language), three aptitude variables (intelligence, verbal, and numerical), and three adaptability variables (influencing people, accepting responsibility for direction, and dealing with people). The motor complexity measure, meanwhile, comes from 20 physical demand variables, including motor coordination, finger dexterity, manual dexterity, eye-hand-foot coordination, spatial perception, form perception, color discrimination, setting limits, and tolerance or standards. Following Autor et al. (2003), the two measures, cognitive and motor complexity, are converted into percentile scores among the all occupations, taking a value between 0 and 1.

1.3.2 National Longitudinal Survey of Youth 1979

The National Longitudinal Survey of Youth 1979 (NLSY79) is particularly suitable for this study because it is a long panel data set which contains detailed individual career information and focuses on the young, when most labor market transactions actually occur (Neal (1999)). The survey includes individuals who are between 14 and 21 years old as of January 1, 1979. Occupations in the NLSY79 are coded using a three-digit Census frame, which consists of 503 distinctive categories. Yamaguchi restricts his samples to male workers who make long-term transitions in the labor market during 1979-2000. A long-term transition means working 30 hours per week or more for three consecutive years during the periods. His final data set includes 2,417 workers' career history, 32,774 person-year observations of occupational choices and 31,157 person-year observations of wages. The DOT occupations are aggregated into the three-digit classifications in order to merge with the NLSY79. Worker characteristics such as race, AFQT (Armed Forces Qualification Test) score, and years of education are also obtained from the NLSY79. Excluding non-workers from the sample may bias the estimators in the event some people lose a job because of a bad match and their wage is missing.

In addition to occupation, wage, workers' pre-labor market characteristics variables constructed in Yamaguchi (2012), I obtained initial asset information from the NLSY79. I focus on money assets such as the savings account of the respondent and his/her spouse. Household assets are recorded after 1985 and once every two years in NLSY79. Therefore, for workers who entered in the labor market between 1979 to 1984, I have information about their wealth level only after they have worked and accumulated assets for some years. For this reason, I construct predicted initial wealth using the information from workers who have records of initial assets at their labor market entry, workers' initial characteristics such as years of educational attainment, AFQT scores, demographics, and their first period labor earnings.

Table 1.1 reports the mean and standard deviation of all variables and Figure 1.1 shows the histogram of the predicted initial wealth data used in this paper. The mean of the AFQT score is 49.079 and the standard deviation is 30.1438. The average years of educational attainment is slightly over 13 years (13.2375) and its standard deviation is 2.5353. The percentage of Hispanics in the sample is about 11%, and about 82% of the sample are whites. Average age at the labor market entry is 21.1386 with a standard deviation of 2.9532. Log Initial asset levels are in 2005 real dollars. The mean is 5.57 and the standard deviation is 2.6359. As mentioned (asset levels are only recorded after 1985, once in two years), only a smaller subset of the full sample (503 out of 2417) have data on initial assets. The summary of wage and occupations show hourly wage rates in 2005 real dollars, and cognitive and motor task choice observed yearly from 1979 to 2000. The mean of the hourly wage rate is 17.6904 with a standard deviation of 10.4820.

Table 1.2 shows more detailed summaries for the panel data. We can see that on average, the hourly wage rate increases continuously from 11.8307 in year 1 to 23.4238 in year 22. The variance of the wage distribution increases in years as well, from 5.7708 in year 1 to 12.3660 in year 22. This is a common finding, earnings profiles spread out over time. The number of observations decreases in year because 'year' indicates the years after labor market entry. A smaller number of data points are observed for longer periods of time.

Table 1.1 also shows the summary of pooled data on occupational choices. The mean of cognitive task choice for all years is 0.5018 and its standard deviation is 0.2645, and the mean and standard deviation for motor tasks is 0.5291 and 0.2487 respectively. Table 1.2 describes how they change over the life cycle. For cognitive choices, we observe increasing trends from 0.4124 to 0.5436, and slightly decreasing trends in motor tasks from 0.5313 to 0.5147 for over 22 years. It is rising for the first 6 years, and starts to decline after. The on-the-job skill accumulation (learning-by-doing) process could be very different for different sets of skills, suggesting that a single accumulation rule for skills in multi-dimension will not be able to successfully illustrate skill changes over the life-cycle. Another possible explanation is that motor skills are likely to depreciate as workers get older, and this skill depreciation effect may dominate skill accumulation in the later periods of the life-cycle. The standard deviations stay roughly the same for both tasks.

1.4 Reduced Form Empirical Evidence on Learning

One important question to address prior to investigating further the impacts that learning about one's true skill level has for a worker is whether learning indeed exists in the labor market. Although imperfect information about ability and learning has been widely discussed in the literature, there has not, in fact, been much empirical evidence to demonstrate its importance. One finding in the literature that suggests learning, is the fact that job mobility decreases with age and tenure (Neal (1999)). And in a recent paper, Arcidiacono et al. (2016) address the fact that those who receive wages in excess of their worker characteristics are more likely to stay in the same occupation. The authors suggest this correlation as evidence for learning.

However, both features can be fully explained through a search model that does not account for learning. Workers keep searching until they find a satisfactory match; hence, probabilistically, job mobility decreases with both age and current wage.

Taking advantage of the continuous task complexity space in Yamaguchi (2012), I first show reduced-form evidence of learning. Using Yamaguchi's data set, I regress the log hourly wage on individual characteristics such as race, education, AFQT scores before labor market entry, occupation-specific experience, and most importantly, the cognitive and motor task requirements of their current job, as well as an interaction term between the two skill requirements. The "surprise" is computed as the wage residual. Even if a positive or negative surprise in wage is informative regarding productivity, it is an overall wage surprise. Workers cannot observe how much of the surprise is from their cognitive skills or from motor skills. However, the relative intensity between cognitive and motor tasks at the current job may be informative for workers to infer the source of this new information; workers who use cognitive (motor) skills more at the current job will learn more about their cognitive (motor) skills than their motor (cognitive) skills.

I use a rough measure of the relative intensity in this section; occupations are either cognitive- or motor-task intensive. If the cognitive task requirement is higher than the motor task requirement in the current occupation, that occupation is called cognitive-task intensive (or "cognitive-intensive"); otherwise, motor-task intensive (or "motor-intensive"). Workers who have cognitive-intensive occupations are expected to learn more about their level of cognitive skill, and workers with motor-intensive occupations will learn more about their level of motor skill. Those who have a cognitive-intensive occupation and receive a positive signal, therefore, are expected to seek occupational moves that require greater cognitive intensity; those who receive a negative signal, by contrast, are expected to move "down" to a less cognitive-intensive job. Similarly, people with motor-intensive occupations are expected to seek future jobs with more motor tasks, once they find (by virtue of a positive signal) that they are capable in that type of skill; however, they would not be expected to move in the same direction with respect to cognitive-intensive work, since cognitive and motor skills reflect different dimensions.

I estimated log hourly wage equations with and without individual fixed effects. The estimated wage equation without fixed effects is:

$$\ln w_{it} = \alpha + X_{1it}\beta_1 + X_{2it}\beta_2 + u_{it} \tag{1.1}$$

from which the signal, or surprise, is calculated as

$$\begin{aligned} \text{signal}_{it} &= \hat{u}_{it} \\ &= \ln w_{it} - \alpha + X_{1it}\hat{\beta}_1 + X_{2it}\hat{\beta}_2 \end{aligned} \tag{1.2}$$

And a panel data regression with fixed effects and the signal are:

$$\ln w_{it} = \alpha_i + X_{1it}\beta_1 + u_{it} \tag{1.3}$$

$$\begin{aligned} \text{signal}_{it} &= \hat{u}_{it} \\ &= \ln w_{it} - \alpha_i + X_{1it}\hat{\beta}_1 \end{aligned} \tag{1.4}$$

where X_1 includes cognitive task x_c, motor task x_m, the interaction term of the two $x_c x_m$, occupational tenure, occupational tenure squared, years of the experience in the labor market and its squared, and X_2 includes AFQT score, years of education, race dummy.

The first column of Table 1.3 shows OLS estimates and the second column shows fixed effect estimates. When the observed occupation is the same as in the previous period and wage data is missing, the wage is assumed to be the same as the previous period. Both regressions show that there is a sizable difference in returns for cognitive and for motor tasks. The coefficients on the interaction term between the two are negative, and occupational tenure has positive effects on the log wage. The OLS regression controls for the AFQT score, years of education, and race dummy variables, and age.

Tables 1.4 and 1.5 show the regression results for cognitive and motor tasks, x_c and $x_m \in (0, 1)$ respectively, chosen in $t + 1$ on the tasks in period t using the wage residual predicted in the OLS regression and the fixed-effects panel data regressions, respectively. Therefore, Tables 1.4 and 1.5 show the direction of occupational movement in each of the two tasks. Dummy variable $D_{c,t} = 1$ indicates cognitive-intensive occupations where $x_{c,t} > x_{m,t}$.

The coefficients on signal$_t$ $\times$ $D_{c,t}$ in Tables 1.4 and 1.5 suggest that a worker who has received unexpectedly high monetary rewards will move up to jobs that require more of the abilities that the worker is currently using compared to the workers in the motor-intensive jobs. On the other hand, those who have received disappointingly low wages adjust themselves into new occupations that require different kinds of skills. Workers in cognitive-intensive sectors tend to move up into more intensive cognitive tasks as their wage residuals increase, while negative shocks may make them choose higher motor tasks instead.

1.5 Model

This section develops a dynamic career choice model that accounts for learning and wealth inequality. Occupations are still defined over the two-dimensional continuous tasks space. Workers observe their current wage as a productivity signal and update their beliefs about their abilities accordingly. Workers are risk-averse and heterogeneous with respect to initial wealth and skill endowments. All information regarding workers' work history is assumed to be public; therefore employers are assumed to have symmetric information. Finally, the labor market is assumed to be competitive.

Both informational friction and risk aversion are crucial for wealth inequality to have a role in the career choice. In the perfect-information case, for example, a worker knows in which occupation he can be most productive and hence knows which career path results in the highest payoffs. Regardless of his risk preference, then, any worker in a perfect-information scenario would choose the occupation that gives the highest future wage streams, to maximize his lifetime budget. Risk preference, in this case, could affect a decision-maker's consumption and savings behavior but not his career choice; therefore wealth would not play a role in occupational choice.

Meanwhile, a worker who is risk-neutral but does not know her ability perfectly will choose an occupation that has the highest expected wage streams regardless how much risk is involved in that choice. A wage-maximizing career path maximizes the risk-neutral worker's lifetime utility as well, and her occupational choice depends only on her own (imperfect) belief in her ability, but not on the wealth in her hands.

If a worker is both risk-averse and has imperfect information about his own ability, however, that worker might not want to choose the wage-maximizing occupation after all, if the wage-maximizing choice were associated with high risk. Workers may be discouraged from actively engaging in learning. Hence, underinvestment in career choice occurs, and the gap between risk-optimal and wage-maximizing occupations could be wider for workers with low wealth under plausible assumptions such as constant relative risk aversion or credit constraints. In effect, workers with greater wealth are more likely to find occupations with better fit, and therefore wealth inequality can increase further still. Additionally, as time passes by, workers who experiment more, learn more about their ability, and so wage inequality may increase even further.

Lifetime income risk, in this model, derives from skill uncertainty; workers make decisions about consumption, savings, and their next-period occupations, all in response to the partial realization of uncertainty, and they adjust their career paths accordingly in order to maximize lifetime utility.

My model consists of the following elements: 1) a wage function which is determined by the choice of tasks, workers' true skills, and a random transitory shock, and 2) a skill accumulation equation which depends on workers' previous skill level, task choices, and a permanent productivity shock on each skill dimension, and 3) a formal description of learning and belief updating process by Bayes Rule. The following subsections describe this model in detail.

1.5.1 Wage function

Both workers and employers have imperfect and symmetric information about workers' skills, and the labor market is assumed to be competitive. Therefore, workers are paid by their marginal value product. The marginal value product of a worker with skill $s_t = (s_{ct}, s_{mt}) \in \mathbb{R}^2$ in an occupation with task complexity $x_t = (x_{ct}, x_{mt}) \in (0,1)^2$ is

$$w_t = \pi(x_t) + q(x_t, s_t) + \epsilon_t, \tag{1.5}$$

where $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ is an independent and identically distributed transitory productivity shock. The output price from task x_t is defined as $\pi(x_t)$, and $q(x_t, s_t)$ is a worker's marginal productivity which depends on the task x_t and skill s_t levels. I assume that the marginal productivity of a worker who is endowed with skill s_t in occupation x_t takes the following form:

$$q(x_t, s_t) = (B_2(\alpha s_t - x_t))' x_t, \tag{1.6}$$

where α is a scalar, and B_2 is 2-dimensional diagonal matrix. Labor productivity is the inner product of excessive skill and task requirement. Note that components in the term $(\alpha s_t - x_t)$ can be negative. If a low skilled worker chooses an occupation that requires much higher task, the low labor productivity will result in low wages.

The output price $\pi(x_t)$ is assumed to be linear in the task requirements.

$$\pi(x_t) = B_0 + B_1' x_t, \tag{1.7}$$

where B_1 is a two dimensional vector. Finally, period t wage w_t can be written as

$$\begin{aligned} w_t &= B_0 + B_1' x_t - x_t' B_2 x_t + g_t \\ g_t &= x_t' B_3 s_t + \epsilon_t \end{aligned} \tag{1.8}$$

where $B_3 = \alpha B_2$. Wage coefficients B_0, B_1, B_2 and B_3, and the distribution of the transitory shocks ϵ_t are known to workers, but they do not observe their true skills s_t and realization of the shock ϵ_t. Therefore, when w_t is unexpectedly high (or low), workers cannot perfectly pin down whether that is because their true skill s_t is high (low) or they were just lucky (unlucky).

By construction, the variance in the wage distribution within an occupation is larger as the job task intensity x_t is higher. For example, for an imaginary occupation $x_{ct} = x_{mt} = 0$, w_t is simply $B_0 + B_1' x_t - x_t' B_2 x_t$ for everyone, regardless of workers' skill s_t. However, as the task intensity x_t rises, the wage depends more and more heavily on the workers' true skill levels s_t and the variance in the wage distribution becomes larger.

If B_1, B_2 and B_3 are positive, for any worker with $s_t > 0$, the expected value of the unknown part of the wage g_t increases with respect to the occupational choice x_t. However, the marginal change in the known part of the wage, $B_1 - B_2 x_t$ decreases with respect to x_t, hence B_2, cost of mismatch (overshooting), provides an incentive not to choose high x_t for workers who believe their true skills s_t are low.

1.5.2 Skill accumulation

Skills accumulate based on the workers' skills in the previous period and the choice of occupations. The following equation shows the process of skill accumulation:

$$\begin{aligned} s_{t+1} &= s_t + A_1' x_t + x_t' A_2 x_t + \eta_t \\ s_0 &= H_0 + H_1 d + \eta_0 \end{aligned} \tag{1.9}$$

Where $\eta_t \sim N(0, \sigma_\eta^2)$ is a iid shock on the skills which reflect a permanent shock in the productivity. Workers know the values of A_1, A_2, and the distribution of the permanent skill shocks, η_t. Initial skills s_0 depend on the worker's characteristics d before the labor market entry and the unknown iid skill shock $\eta_0 \sim N(0, \sigma_{\eta 0}^2)$. A_0 , A_1, H_0, s_t, η_t, and σ_η are 2 dimensional vectors, and A_2 is 2×2 diagonal matrix.

1.5.3 Learning

Workers do not exactly know their skill levels. Instead, workers have beliefs about their skills and update the belief from the wage realization each period. Wage depends on the labor productivity $q(x_t, s_t)$, so it is informative about skills. Workers observe a signal g_t, the sum of the last two terms in the wage equation $g_t := (B_3 x_t)' s_t + \epsilon_t$, but they do not know the decomposition. Three unobservable and independent factors contribute to the signal g_t; Cognitive skills, motor skills and the iid productivity shock ϵ_t.

$$g_t = B_{3c} x_{ct} s_{ct} + B_{3m} x_{mt} s_{mt} + \epsilon_t, \tag{1.10}$$

where a worker's prior belief before signal g_t on each term is

$$\begin{aligned} B_{3c} x_{ct} s_{ct} &\sim N(B_{3c} x_{ct} \hat{s}_{c,t-1}, (B_{3c} x_{ct})^2 \sigma^2_{c,t-1}), \\ B_{3m} x_{mt} s_{mt} &\sim N(B_{3m} x_{mt} \hat{s}_{m,t-1}, (B_{3m} x_{mt})^2 \sigma^2_{m,t-1}), \\ \epsilon_t &\sim N(0, \sigma^2_\epsilon) \end{aligned} \tag{1.11}$$

A worker's prior beliefs on s_t are the expected skills given all information available up to period $t-1$, $\hat{s}_{t-1} = E(s_{t-1}|g_{t-1}, x_{t-1})$ and the variance for each skill is $\sigma^2_{c,t-1}, \sigma^2_{m,t-1}$. Workers update their beliefs on the cognitive and motor skills by Bayes rule.

By construction, the signal g_t is weighted by the task complexity x_t. Those who exert one skill more intensively than another gain more information on the skill that is used more intensively. For example, in the extreme case of $x_t = [1, 0]$, the occupation requires cognitive skill only, hence the worker will gain information on her cognitive skill but not motor skill by the signal g_t. For notational simplicity, let $\tau_{ct}, \tau_{mt}, \tau_\epsilon$ be

$(B_{3c}x_{ct})^2\sigma^2_{c,t-1}, (B_{3m}x_{mt})^2\sigma^2_{m,t-1}$, and σ^2_ϵ respectively.

$$\begin{aligned} E(B_{3c}x_{ct}s_{ct}|g_t) &= B_{3c}x_{ct}\hat{s}_{c,t-1} + \frac{\tau_{ct}(g_t - B_{3c}x_{ct}\hat{s}_{c,t-1} - B_{3m}x_{mt}\hat{s}_{m,t-1})}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \\ &= \frac{\tau_{ct}(g_t - B_{3m}x_{mt}\hat{s}_{m,t-1}) + (\tau_{mt}+\tau_\epsilon)B_{3c}x_{ct}\hat{s}_{c,t-1}}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \end{aligned} \tag{1.12}$$

Hence, the posterior belief on cognitive skill given the noisy signal g_t is

$$E(s_{ct}|g_t) = \frac{(\tau_{mt}+\tau_\epsilon)\hat{s}_{c,t-1} + \tau_{ct}\frac{(g_t - B_{3m}x_{mt}\hat{s}_{m,t-1})}{B_{3c}x_{ct}}}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \tag{1.13}$$

Similarly, the updated belief on motor skill is given by:

$$E(s_{mt}|g_t) = \frac{(\tau_{ct}+\tau_\epsilon)\hat{s}_{m,t-1} + \tau_{mt}\frac{(g_t - B_{3c}x_{ct}\hat{s}_{c,t-1})}{B_{3m}x_{mt}}}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \tag{1.14}$$

The updated variance of cognitive skill is

$$\begin{aligned} var(B_{3c}x_{ct}s_{ct}) &= \tau_{ct} - \frac{\tau_{ct}^2}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \\ &= \frac{\tau_{ct}\tau_{mt}+\tau_{ct}\tau_\epsilon}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \end{aligned} \tag{1.15}$$

$$\begin{aligned} var(s_{ct}) \equiv \sigma^2_{ct} &= \frac{1}{(B_{3c}x_{ct})^2}\ \frac{\tau_{ct}\tau_{mt}+\tau_{ct}\tau_\epsilon}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \\ &= \frac{\sigma^2_{c,t-1}(\tau_{mt}+\tau_\epsilon)}{\tau_{ct}+\tau_{mt}+\tau_\epsilon} \end{aligned} \tag{1.16}$$

Similarly, the updated variance of motor skill is

$$\begin{aligned} var(s_{mt}) \equiv \sigma_{mt}^2 &= \frac{1}{(B_{3m}x_{mt})^2}\,\frac{\tau_{ct}\tau_{mt}+\tau_{mt}\tau_{\epsilon}}{\tau_{ct}+\tau_{mt}+\tau_{\epsilon}} \\ &= \frac{\sigma_{m,t-1}^2(\tau_{ct}+\tau_{\epsilon})}{\tau_{ct}+\tau_{mt}+\tau_{\epsilon}} \end{aligned} \tag{1.17}$$

1.5.4 Bellman Equation

Combining all the components listed in this section, Bellman equation for a decision maker is formulated as:

$$\begin{aligned} V_t(m_t, \hat{s}_t, \sigma_t^2) &= \max_{c_t, x_{t+1}} u(C_t) + E_t(V_{t+1}(z_{t+1}, \hat{s}_{t+1}, \sigma_{t+1}^2)) \\ &= \max_{c_t, x_{t+1}} \frac{{C_t}^{1-\rho}}{1-\rho} + E_t(V_{t+1}(z_{t+1}, \hat{s}_{t+1}, \sigma_{t+1}^2)) \end{aligned} \tag{1.18}$$

$$\begin{aligned} s.t. \quad a_t &= z_t - c_t \geq 0 \\ z_{t+1} &= a_t + w_{t+1} \\ w_{t+1} &= B_0 + B_1' x_{t+1} - x_{t+1}' B_2 x_{t+1} + g_{t+1} \\ \hat{s}_{t+1} &= E_t(s_t|g_t) + A_1 x_{t+1} + x_{t+1}' A_2 x_{t+1} \\ \sigma^2_{j,t+1} &= \frac{\sigma^2_{jt}(\tau_{-j,t+1} + \tau_\epsilon)}{\tau_{j,t+1} + \tau_{-j,t+1} + \tau_\epsilon} + \sigma^2_{\eta j}, \;\; j = \{c, m\} \\ x_t &\in (0,1)^2 \end{aligned} \tag{1.19}$$

where $g_{t+1} \sim N(x_{t+1}' B_3 \hat{s}_t, (x_{t+1}' B_3 \sigma_t)^2 + (\sigma_\epsilon)^2)$, a_t is the end of the period t asset, amount of assets left after wage realization and the consumption decision in period t. And z_t is wealth, or cash-on-hand, available to use for consumption in the beginning of the period t. Individual workers choose current period consumption, and next period occupation to maximize expected lifetime utility.

Using the backward induction, I numerically solve for the three choice variables which simultaneously satisfy the three first order conditions with respect to the each choice variable. In the final period T, the only choice that workers have is consumption. Workers exhausts their total wealth in the last period.

$$\begin{aligned} & V_T(m_T, \hat{s}_T, \sigma^2_T) = \max_{C_T} u(C_T) \\ & s.t. \; C_T = a_T + w_T \end{aligned} \tag{1.20}$$

One period before, the optimal choices for workers satisfy the following three first order conditions for C_{T-1}, $x_{c,T}$, $x_{m,T}$ respectively.

$$\begin{aligned} u'(C_{T-1}) =& E_t(V'_T(z_T, \hat{s}_T, \sigma^2_T)) \\ =& E_t(u'(C_T)) \quad \text{By Envelope Theorem} \end{aligned} \tag{1.21}$$

$$E_{T-1}(\frac{\partial V_T}{\partial z_T}(B_{1c} - 2B_{2c}x_{cT} + B_{3c}s_{cT} + B_{3c}x_{cT}\frac{\partial s_{cT}}{\partial x_{cT}})) = 0 \tag{1.22}$$

$$E_{T-1}(\frac{\partial V_T}{\partial z_T}(B_{1m} - 2B_{2m}x_{mT} + B_{3m}s_{mT} + B_{3m}x_{mT}\frac{\partial s_{mT}}{\partial x_{mT}})) = 0 \tag{1.23}$$

Equations (22) and (23) do not contain $\frac{\partial V_T}{\partial \hat{s}_T}$ and $\frac{\partial V_T}{\partial \sigma^2_T}$ terms because the beliefs of each skill do not have any effects in the final period T, since the only choice variable is consumption at T.

Finally, for the periods $t = 1, ..., T-2$, The first order condition with respect to $x_{c,t+1}$ is:

$$E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}\frac{\partial z_{t+1}}{\partial x_{c,t+1}} + \frac{\partial V_{t+1}}{\partial \hat{s}_{t+1}}\frac{\partial \hat{s}_{t+1}}{\partial x_{c,t+1}} + \frac{\partial V_{t+1}}{\partial \sigma^2_{t+1}}\frac{\partial \sigma^2_{t+1}}{\partial x_{c,t+1}}) = 0 \tag{1.24}$$

To show $\frac{\partial V_{t+1}}{\partial \hat{s}_{t+1}} = 0$, take a partial derivative of each side with respect to $\hat{s}_t$.

$$\begin{aligned}\frac{\partial V_t}{\partial \hat{s}_t} &= E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}\frac{\partial z_{t+1}}{\partial \hat{s}_t} + \frac{\partial V_{t+1}}{\partial \hat{s}_{t+1}}\frac{\partial \hat{s}_{t+1}}{\partial \hat{s}_t} + \frac{\partial V_{t+1}}{\partial \sigma^2_{t+1}}\frac{\partial \sigma^2_{t+1}}{\partial \hat{s}_t}) \\ &= E_t(\frac{\partial V_{t+1}}{\partial \hat{s}_{t+1}}\frac{\partial \hat{s}_{t+1}}{\partial \hat{s}_t}) \\ &= \frac{\tau_{ct}}{\tau_t}E_t(\frac{\partial V_{t+1}}{\partial \hat{s}_{t+1}})\end{aligned} \tag{1.25}$$

Since equation (1.25) holds for all periods,

$$\begin{aligned}\frac{\partial V_{T-1}}{\partial \hat{s}_{T-1}} &= \frac{\tau_{c,T-1}}{\tau_{T-1}}E_{T-1}(\frac{\partial V_T}{\partial \hat{s}_T}) \\ &= \frac{\tau_{c,T-1}}{\tau_{T-1}}E_{T-1}(\frac{\partial u(z_T - C_T + w_T)}{\partial \hat{s}_T}) \\ &= 0\end{aligned} \tag{1.26}$$

Similarly, $\frac{\partial V_{t+1}}{\partial \sigma^2_{t+1}} = 0$, and the first order condition for cognitive task choice $x_{c,t+1}$ is reduced to:

$$E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}\frac{\partial z_{t+1}}{\partial x_{c,t+1}}) = E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}(B_{1c} - 2B_{2c}x_{c,t+1} + B_{3c}s_{c,t+1} + B_{3c}x_{c,t+1}\frac{\partial s_{c,t+1}}{\partial x_{c,t+1}})) = 0 \tag{1.27}$$

Using the same process, the first order condition for motor task $x_{m,t+1}$ is again reduced to:

$$E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}\frac{\partial z_{t+1}}{\partial x_{m,t+1}}) = E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}(B_{1m} - 2B_{2m}x_{m,t+1} + B_{3m}s_{m,t+1} + B_{3m}x_{m,t+1}\frac{\partial s_{m,t+1}}{\partial x_{m,t+1}})) = 0 \tag{1.28}$$

Intuitively, beliefs affect the value function only through choices. Given a fixed occupational choice, having a higher or lower belief about ability does not change incomes, or the current and future utility values. Finally, the first order condition with respect to c_t is:

$$u'(C_t) = E_t(u'(C_{t+1})) \tag{1.29}$$

Assuming $A_{1c}, A_{1m}, A_{2c}, A_{2m} = 0$ for simplicity, equations (22), (23), (27), and (28) imply that the optimal choices of x_{ct+1} and x_{mt+1} for any $t < T$ are:

$$\begin{aligned} x^*_{ct+1} &= \frac{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}(B_{1c} + B_{3c}s_{ct+1}))}{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}(2B_{2c}))} \\ x^*_{mt+1} &= \frac{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}(B_{1m} + B_{3m}s_{mt+1}))}{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}}(2B_{2m}))} \end{aligned} \tag{1.30}$$

As long as $x^*_{ct+1}, x^*_{mt+1} \in (0, 1)$, the optimal occupational task x_j is decreasing in B_{2j} which the cost of mismatch between skill and task in the wage equation (1.8) , and increasing in B_{1j} and B_{3j}, which are the reward for the unit of tasks and the coefficient on the interaction term between the skill and the chosen task.

In the perfect information about the skills case, where the only remaining uncertainty is in the idiosyncratic wage shock (equation (1.5)), the optimal occupational choices in equation (1.30) are simplified to:

$$\begin{aligned}
x^P_{ct+1} &= \frac{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(B_{1c} + B_{3c}s_{ct+1})}{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(2B_{2c})} = \frac{B_{1c} + B_{3c}s_{ct+1}}{2B_{2c}} \\
x^P_{mt+1} &= \frac{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(B_{1m} + B_{3m}s_{mt+1})}{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(2B_{2m})} = \frac{B_{1m} + B_{3m}s_{mt+1}}{2B_{2m}}
\end{aligned} \tag{1.31}$$

In this case, the optimal occupation choices depend only on the workers true skill and the coefficients in the wage function.

If skills are unknown but workers are risk neutral, hence the utility function and value function are linear, the equation (1.30) is reduced to:

$$\begin{aligned}
x^N_{ct+1} &= \frac{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(B_{1c} + B_{3c}E_t(s_{ct+1}))}{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(2B_{2c})} = \frac{B_{1c} + B_{3c}\hat{s}_{ct}}{2B_{2c}} \\
x^N_{mt+1} &= \frac{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(B_{1m} + B_{3m}E_t(s_{mt+1}))}{E_t(\frac{\partial V_{t+1}}{\partial z_{t+1}})(2B_{2m})} = \frac{B_{1c} + B_{3m}\hat{s}_{mt}}{2B_{2m}}
\end{aligned} \tag{1.32}$$

Again, in this case, the optimal occupations are determined only by the coefficients in the wage function and the mean of the skill beliefs.

However, if there are uncertainties and risk aversion, the first term inside the expectation in equation (1.30), $\frac{\partial V_{t+1}}{\partial z_{t+1}}$, cannot be dropped, and the solution will depend on the curvature of the utility function with respect to consumption.

Workers face wage risks from two sources, from unknown skills s_c and s_m, and a transitory wage shock ϵ. Given any current belief $(\hat{s}_t, \sigma_t^2)$, the distribution of the unknown part of the future wage w_{t+1} is:

$$g_{t+1} \sim N(x'_{t+1}B_3\hat{s}_t, (x'_{t+1}B_3\sigma_t)^2 + (\sigma_\epsilon)^2) \tag{1.33}$$

Workers expect higher wages when $\hat{s}$ is higher, and larger variances when their belief is noisier (σ_t^2). Workers can control the size of the wage risk that comes from unknown skills through occupational choice. For example, in an extreme case, if a worker is particularly averse to wage fluctuations, she can minimize her wage risk (variance) to the minimum level σ_ϵ^2 by choosing $x_{c,t+1} = x_{m,t+1} = 0$. In doing so, however, this worker does not learn anything about her skills, and her expected skills in period $t+1$ will remain the same as in the current period.

As long as B_3 and $\hat{s}_t$ are positive, an increase in x_{t+1} will raise both the mean and the variance of the unknown part of the wage g_{t+1}, and the marginal effect on the known part of the wage is $B_1 - 2B_2x_{t+1}$. If absolute risk aversion is decreasing, then the risk premium declines with respect to wealth, and hence the optimal occupational choice x_{t+1} will be higher when workers are rich, given the same beliefs. Therefore, workers choose occupations x_{t+1} not only by their wage coefficients and beliefs, but also by taking their risk preferences and wealth levels into account.

There is not a closed-form solution in this case, and it will be numerically solved by the algorithm introduced in the following subsection.

1.5.5 Algorithm to Solve the Model

Calculating the optimal amount of risk to take jointly with savings decisions in a multi-dimensional space is a difficult problem, which cannot be solved without complicated numerical computations. To speed up the calculation, I transform the three dimensions of continuous controls, consumption and two tasks, into a sequence of two optimization problems. For any given levels of assets and belief, I first find the optimal task choices that satisfy the first-order conditions in equations (27) and (28) simultaneously. With the optimal occupation policy function in hand, I calculate the expected future income for the five-dimensional grid of the state space, and this allows me to solve for the simple consumption choice, given current assets and expected income, the latter of which is derived using the occupation policy function.

To find the optimal tasks that simultaneously satisfy the two first-order conditions, I use Broyden's method (Broyden (1965)), which is an extension of the secant method of root finding to higher dimensions. The key idea behind Broyden's method is to calculate the whole Jacobians only once and to update using the secant information at other iterations. For root finding problems with simple Jacobians such as linear optimizations, Newton's method is more suitable for the point of view of the time effectiveness, because it converges in fewer iterations than Broyden's method. However, Newton's method requires repeated evaluation of the system of Jacobians for each iteration, Broyden's method can reach the optimum faster in complicated, non-linear optimization problems of this kind. I solve for the numerical optimums x_{ct} and x_{mt}

that satisfy the first order conditions given the fixed grids of the five state variables, $(z_t, \hat{s}_{ct}, \sigma^2_{ct}, \hat{s}_{mt}, \sigma^2_{mt})$ (equation(30)). I obtain the policy functions for the two tasks choices by spline interpolation.

For the second step, I use the Endogenous Grid Method proposed by Carroll (2006). In this step, the objective is to find the value C_t, which has the same marginal valuation for each of the ends of the period asset value a_t using the first-order condition. And obtain z_t simply as the sum of a_t and C_t. As opposed to the usual solution methods that define ex-ante grids for z_t and then perform root-finding routines to find corresponding optimal C_t, the Endogenous Grid Method does not require a root-finding process; hence, it speeds up the numerical computation greatly. I numerically calculate the marginal expected value (EV_t') given the expected income w_t at the optimal occupation for each set of states $(z_t, \hat{s}_{ct}, \sigma^2_{ct}, \hat{s}_{mt}, \sigma^2_{mt})$ to find the optimal consumption C_t.

Finally, I evaluate the outside the grid chosen for solution by spline interpolation.

1.6 Estimation Results

I jointly estimate all the structural parameters; risk aversion, wage, and skill accumulation coefficients, initial wealth and initial skills, using Simulated Method of Moments. I simulate the career and savings choices of 12,085 workers (5 replications of 2,417 profiles observed in the NLSY79) using the observed individual backgrounds and work histories for 20 years after the labor market entry.

For simulation, I made the following final period assumptions. First, workers do not change occupations after the first 20 years in the labor market. Second, workers work for 20 more years in the same occupation afterwards. Finally, it is assumed that workers expect to live for 20 more years after retirement so that workers do not use up all their savings at that time of the retirement.

I construct 150 moments, including the mean of wages and task choices of each 1-year period after labor market entry for 20 years of the data. I use conditional moments for wages and task choices on the two different levels of educations: low if the final education is high school graduate or less, and high if some college or above. The estimates $\hat{\theta}$ are defined by

$$\hat{\theta} = \arg\min_{\theta} \left\{ \sum_{k=1}^{K} \Big((M_k^d - M_k^s(\theta))^2 / \mathrm{Var}(M_k^d) \Big) \right\} \tag{1.34}$$

where (M_k^d represents kth data moment and $M_k^s(\theta)$ is kth simulated moment at the parameter value θ. I compute asymptotic standard errors following Gourieroux et al. (1993).

1.6.1 Parameter Estimates

One of the key elements in this model is the stochastic process of wages, because that is a main source of uncertainty. Workers observe the productivity signal $g_t =$

$B_{3c}x_{ct}s_{ct} + B_{3m}x_{mt}s_{mt} + \epsilon_t$ and update their beliefs to make a future occupational choice. The mean-zero idiosyncratic shock ϵ_t with standard deviation $\sigma_\epsilon = 0.5045$, reported in Row 5 in Table 1.6, guarantees that the signal is noisy. Therefore, workers cannot immediately pin down their skills after one year of work experience.

Table 1.6 shows that the reward for an additional unit of cognitive task, $B_{1c} = 14.5424$, is much higher than for motor task, $B_{1m} = 5.3875$, a finding consistent with the reduced-form results OLS and panel data fixed effect wage regressions in Table tab1:wagereg. Similarly, the coefficient on the interaction terms between task and workers' true skill is larger for cognitive tasks than for motor tasks, where $B_{3c} = 27.3512$ and $B_{3m} = 20.6370$. However, more interestingly, the cost for overshooting – that is, the cost of choosing a higher task complexity when one's true ability is low – is also much higher for cognitive tasks ($B_{2c} = 28.5607$) than for motor tasks ($B_{2m} = 19.2269$). Therefore, even though the compensation for cognitive tasks is higher than for motor tasks, having an occupation that requires high cognitive intensity may not be an attractive choice for risk-averse workers if the variance, which is uncertainty, in their cognitive skill belief is large.

Table 1.6 also reports the CRRA risk aversion coefficient, $\rho = 3.8666$, which is strictly greater than 0 and implies that workers are risk averse. Previous literature typically finds that the risk aversion coefficient for CRRA utility function is in the range of 1 to 5 (MaCurdy et al. (1990), Friedberg (2000)). The estimated risk aversion coefficient implies that when workers have uncertainty about their own skills, they will under-invest; they will choose lower-intensity tasks in situations with uncertainty, compared with situations in which their skills are perfectly known. Moreover, this inefficiency (due to uncertainty) will decrease with workers' wealth level.

Table 1.7 shows the estimates for the initial skills and the skill accumulation parameters. Cognitive skills accumulate almost linearly along the choice of cognitive task, where $A_{1c} = 0.0479$ and $A_{2c} = 0.0023$. The coefficient on the quadratic term of cognitive task, A_{2c}, is close to zero and not statistically significant. However, motor skill accumulation is concave in the motor task choice, where $A_{1m} = 0.0663$ and $A_{2m} = -0.0742$. Therefore, motor skill accumulates more as the choice of the motor task is larger. However, the marginal benefit of motor skill accumulation for choosing higher motor tasks diminishes as the motor task itself increases.

Idiosyncratic skill accumulation shocks, reported in the 3rd row in Table 1.7, accounts for the permanent shock in workers' productivity. The estimation results show that the standard deviation of the distribution of cognitive skill accumulation shock is 1.1081, while the standard deviation for the distribution of the motor skill accumulation shock is smaller, 0.0580.

I use two pre-labor market entry variables to determine initial skills: AFQT score and years of education. Both variables have a positive coefficient on the initial cognitive skill, where $H_{1c} = 0.0027$ and $H_{2c} = 0.1028$. On the other hand, both variables have a negative coefficient on the initial motor skill, $H_{1m} = -0.0012$ and $H_{2m} = -0.0519$, while the coefficient of AFQT on the motor skill is not statistically significant.

Row 8 of Table 1.7 reports the standard deviation of initial belief distribution for each of the skill dimensions. The standard deviation of the initial belief distribution for cognitive skill is 0.3212, while for motor skill it is 0.3866. Therefore, on average, workers start with a higher degree of uncertainty about their motor skills than their cognitive skills at the time of labor market entry. However, because of the higher uncertainty in cognitive skill accumulation (compared to motor skill accumulation), the uncertainty about motor skills resolves faster than it does for cognitive skills over the life cycle.

1.6.2 Model Fit and Implications

The model's prediction fits the observed data well overall. Figure 1.2 shows the life-cycle profiles of occupations for each education group, where "high education" means that the highest level of educational attainment was some college education or higher, and "low education" means that the highest level attained was high school graduate or lower.

Cognitive task choices in Figure 1.2 (a) show an increasing pattern over time for both education groups, with the large gap between the two. Rather surprisingly, the average cognitive task choice for the low-education group continuously rises over the life cycle, while cognitive task choices for the high-education group increase rather sharply during the early periods of their careers and then stay constant after about 10 years post-labor market entry. As a result, the gap between the cognitive task choices of the two groups slightly decreases over the life cycle, both within the data and in the model simulation.

Figure 1.2 (b), then, shows the life-cycle profiles of the average motor task for each education group. The low-education group always chooses higher motor tasks than the high-education group does, on average. However, average motor task choice does not show generally increasing patterns for both groups; rather, the groups' motor task choices stay constant overall. To be even more precise, the low-education group's average motor task choice increases slightly in the early periods of their careers, and decreases afterwards; for the higher-education group, their motor task choices continue to diminish slightly over all the years. Still, the overall changes in motor task choices are very small compared to the changes previously observed in cognitive tasks.

The life-cycle profiles of the hourly wage rates are presented in Figure 1.3. On average, both education groups receive higher wages as their experience in the labor market increases, though it should be noted that both data and simulation results show that the wage gap between the two education groups widens over life cycle. For example, the high-education group, on average, received about $3 more per hour compared to the low-education group in the first year of labor market entry. However, by the 20th year, the difference in hourly wages between the two groups is around $10. This is a common finding in the literature: wage gaps widen over time.

The findings in Figure 1.2 and Figure 1.3 suggest that the widening wage gap is not due to highly-educated workers choosing more complex tasks over time, but rather to the dynamic effect of on-the-job skill accumulation and learning. Highly-educated workers tend to choose higher cognitive tasks in the early periods of the life cycle, and through the skill accumulation and learning channels, this choice returns even higher cognitive skills for highly-educated workers.

While workers' true skills or beliefs are not observed in the data, the simulation results in Figure 1.4 show the progressions of the workers' beliefs about their skills; the means and the standard deviations of their beliefs. Figure 1.4 (a) reveals a widening gap in the means of the cognitive skill beliefs held by the two education groups, which drives the increasing wage gaps between the groups in turn. In the 20th year, the gap between the means of cognitive skills are about 0.25 larger compared to the first year. The 0.25 difference in the cognitive skills accounts for about \$4.78 of wage differences when $x_c = 0.7$. By contrast, the means of motor skill belief in both groups stays constant over the life cycle, while the low-education group shows small increments and the high-education group shows the opposite. Panels (c) and (d) in Figure 1.4 depict the standard deviations of beliefs over time. For both cognitive and motor skills the uncertainties drop for the first 8 years after entering the labor market and stay roughly constant after.

Figure 1.5 presents the hourly wage profiles across the quartiles of the wage distribution to show that the simulation results can replicate the dispersion of wages in data. The model prediction fits the data well, while the main discrepancy lies in the bottom 25% of the high-education group's income distribution. This accounts for the fact that simulated average wage profiles for high education in Figure 1.3 are slightly lower than the actual data show. As many previous studies on income inequality document, figure 1.4 shows that the variance of the income distribution among the highly-educated workers is much larger than the variance in the income distribution for the low-educated group.

1.6.3 Benefits of Learning

In this section, I analyze the relative importance of learning and skill accumulation for lifetime earnings. To separate the two dynamic effects of career choice, I simulated the model without any of the learning effects described in Section 5.3. Workers' skills can increase over time due to the on-the-job skill accumulation, and their beliefs change accordingly taking skill accumulation effects into account. However, they do not adjust their beliefs based on the productivity signals.

Figure 1.6 shows the average wage profiles of the workers with and without learning effects. The solid line represents the baseline model with both learning and skill accumulation, and the dashed line shows the simulation results without learning effects. Workers in the two cases start with the same beliefs and true skills, therefore the starting wages are the same. The overall increasing trends are also shown in both scenarios. However, when workers update their beliefs based on the productivity signals to allocate themselves into the occupations that fit better to their skills, they can earn much more. The baseline model with the learning effects show over 20% increases in the hourly wages 10 years after entering the labor market.

1.6.4 Under-Investment in Career Choice and Distributional Effects

In this section, using the estimated parameters, I analyze the distributional effects of under-investment in occupational choices, which I define as a gap between the utility-maximizing and income-maximizing occupational choices. The discrepancy between the two choices occurs due to a combination of risk aversion and informational friction (i.e., skill uncertainty). Even if workers expect to earn the highest income in a certain occupation given their beliefs about their skills, that occupation still might not be the optimal choice for them if the choice involves too much risk. Every risk-averse worker with uncertainty will under-invest. However, the size of this inefficiency will be larger for workers with low wealth if their risk preferences display decreasing absolute risk aversion; if they find the same amount of monetary loss more hurtful when they are poor compared to times they are rich.

Figure 1.7 graphically describes the inefficiencies in career choice. The dashed line represents perfectly informed workers' cognitive task choices for different asset levels given a fixed level of true skill. Not surprisingly, these workers' occupational choices only depend on their true skills because wages are only determined by skills, occupations, and idiosyncratic shocks. Therefore, workers who know their skill levels choose their occupations regardless of their current assets. Workers who have uncertainty about their skills, however, choose less cognitive tasks at all asset levels, given the same beliefs and the same true skills. Furthermore, we can see that the discrepancy between the utility-maximizing and income-maximizing choices is larger when current asset level is low. Figure 1.7 depicts only one dimension of the two skills, however, we can expect the same patterns for the motor tasks as well.

This inefficiencies due to the informational friction causes income losses through two channels: current wage drops and the loss in continuation values. The current wage drop is a direct result of choosing less-complex (i.e., easier) occupations. Given any fixed level of true skills, choosing any occupation other than the wage-maximizing occupation returns lower expected wages in the current period.

The second channel, the losses in continuation values, includes two different dynamic effects: skill accumulation and learning. The skill accumulation parameters in Table 1.8 suggest that workers in a more demanding occupation today will accumulate additional skills in both skill dimensions through on-the-job skill accumulation. This effect is more drastic for cognitive tasks than motor tasks.

Finally, workers learn more about their true skills when they exert their skills more. The productivity signal $g_t = B_{3c}x_{ct}s_{ct} + B_{3m}x_{mt}s_{mt} + \epsilon_t$ in equation (1.13) is weighted by the current occupation choice. For example, if a worker in the hypothetical occupation requires no cognitive skills at all, $x_{ct} = 0$, then this worker knows that g_t only consists of the productivity generated by her motor skills and the idiosyncratic shock, because she knows that she chose $x_{ct} = 0$. Hence, she will not learn any new information about her cognitive skills, and her updated cognitive skill (given the signal g_t) will be exactly the same as her previous expectation, as in equation (1.16). In addition, equations (1.17) and (1.18) demonstrate that the updated variances in skill beliefs become smaller as the chosen occupations themselves are larger. Therefore, workers who choose more intensive occupations will have more precious information about their true ability.

Hence, all of this to say, workers who choose a more intensive occupation today ultimately have bigger chances of finding themselves in even higher positions in the future, through these two dynamic effects.

To measure the inefficiency in career choices by wealth, I simulate occupational choices for over 20 years of the life cycle for perfectly informed workers and compare the resulting wage profiles with the baseline model from the estimated parameters by the first-period wealth levels. The first column in Table 1.8 shows the wage profiles for the low-wealth group. The direct effect of the wage drops in the first period is rather sharp for this group. Without skill uncertainty, choosing wage-maximizing occupations, on average, returns them \$9.5202 per hour, while the optimal choices under uncertainty yield only \$7.1563.

After the first period of work experience and updating beliefs, the differences between the two wage profiles are much smaller in each wealth group, compared to the first period. However, the difference remains higher in the lower-wealth group. For the higher-wealth group, by contrast, the differences between the two wage profiles are smaller, both in the first period and throughout the life cycle. We can observe only a small loss, \$0.2690 per hour, in the last period of the last two columns.

1.7 Policy Implication: Long-Run Effect of Baby Bonds

The Baby Bonds policy[1] has been recently proposed to reduce the wealth gap in the U.S. The main idea of the policy proposal is that a $1,000 savings account would be opened at birth for every child in the U.S. and that children in low-income households would get an additional deposit of up to $2,000 in their account each year. At the age of 18, each person would receive the account, which would be worth, at most, $46,215, including interest. This fund could be used for wealth-building purposes only, such as pursuing a higher education, buying a house, or starting a business.

Using the model, I simulate the long-term effects of the Baby Bonds policy at two different levels of funds: annual supplement of $1,000 and annual supplement of $2,000, which would be worth $23,948 and $46,215, respectively, 18 years after the account openings. The proposal is intended to provide different amounts of annual supports from $0 to $2000 based on the household income levels during the account recipients' childhoods. However, given the limitations in NLSY79 data, I cannot observe parents' income profiles from the moment that each person was born. Therefore, I assume that the same amount of funds is given to everybody, and I add the amount to workers' original initial assets holdings before labor market entry.

This model does not take into account the effects of achieving higher education or buying houses to increase one's assets, but rather evaluates the other side of this

[1]American Opportunity Accounts Act, S.3766–115th Congress (2017-2018). Retrieved from https://www.congress.gov/bill/115th-congress/senate-bill/3766/

policy's potential impact: namely, its potential to provide a safety net for young adults to experiment and discover the career that best matches their skill level. Although this model can potentially be extended to the choices related to wealth-building activities, the current model does not include educational attainment, housing purchases, or business startup as endogenous choice variables. However, considering that all these choices can have positive long-term effects on a person's lifetime earnings – either through increases in initial skills, through additional wealth, or both – the simulation results reported in Table 1.9 can serve as a lower bound of the policy effects in alleviating income inequality.

Table 1.9 reports the effect of the additional (i.e., Baby Bonds) funds on income inequality over the life cycle. Each row in Table 1.9 presents the average annual income ratio between the bottom and the top of the first-period wealth distribution; bottom 50% to top 50%, bottom 25% to top 25%, and bottom 10% to top 10%. The results imply that the Baby Bonds policy would likely have a large, long-term effect in reducing income inequality over the life cycle. $1000 of annual funds for 18 years, which sum up (with interest) to $23,948 would increase the income ratio between the bottom 50% and top 50% from 0.5131 to 0.5157, while they would increase the income ratio between the bottom 25% and top 25% of initial wealth groups by 1.5%. And $46,215 (the upper limit of the Baby Bonds proposal) would increase the bottom 50% to top 50% income ratio by 3% and increase the bottom 25% to top 25% income ratio by 9.2%. The biggest impact is on the lowest decile of the wealth distribution. Because the inefficiencies due to skill uncertainty and risk preference are largest for the people with the lowest wealth, equal amounts of additional funds from the Baby Bonds have the biggest effects for them. $23,948 of funds will increase the income ratio between the bottom 10% and top 10% of wealth groups, from 0.2466 to 0.2561, and $46,215 will increase it to 0.3022.

1.8 Possible Extensions of the Model

In this section, I discuss some of the elements that were not included in the current model but have the potential to draw interesting results once incorporated.

1.8.1 Job Preferences

The recent literature has documented that non-pecuniary job preferences are one of the important factors for college major and occupational choices (Beffy et al. (2012), Wiswall and Zafar (2016)). Indeed, omitting job preferences from this model may have resulted in the biased estimators across different demographic groups. I did try a specification with random assignments of task preferences in the current model; however, the preference parameter estimates were not significant and close to zero. It is possible that such a result was due to the limitations of the data used in this paper; these data simply do not include good measures for individual-specific, pre-determined job preferences, so instead, I relied only on the individual work history (from the panel nature of the data) for the identification. Therefore, it is possible that the pre-determined differences in task preference may have appeared as differentials in workers' initial skills and beliefs. In other words, the model may have interpreted that people believe they are good at the tasks they like – which may be only partially true. Although the effect of job preferences is not the main focus of this article, the current model can be easily extended to include them. Such an extension would be especially interesting for studies concerning the comparison between broader demographic groups such as male and female, immigrants and non-immigrants, or domestic and foreign labor supply.

1.8.2 Moving Costs Across Occupations

Another interesting element worth discussing is the moving cost that occupational mobility entails. In particular, the moving cost is relatable if there are utility costs to moving; that is, if people prefer to stay in one occupation, or if there are monetary costs attendant to obtaining new skills for new jobs, such as retraining or education costs. In both cases, the role of wealth in occupational choice will be strengthened, and we are likely to see stronger distributional effects and income inequalities as a result.

1.8.3 Probability of Successful Match

This current model, furthermore, makes an important assumption about the worker-job match. Namely, it assumes that once workers choose occupations (though their earnings in the chosen occupations will depend on their true skills), they will certainly find a job within that occupation. In other words, the model assumes that there is no mismatch that results in unemployment. Once we introduce the probability of a match as a variable, along which the probability of the match declines as a worker's true skill level diverges further from (or sinks lower than) the skills required by a given occupational choice, then the income risks that workers face when they choose occupations will be larger, and again the role of wealth in occupational choice will be even more important. Such an extension can be interesting for studies that focus on unemployed job seekers; it may provide an interpretation for the role of wealth in unemployed people's occupational choices, and for the resulting match outcomes in terms of match qualities, new-job earnings, or unemployment duration.

1.9 Conclusion

In this paper, I construct a structural model to analyze the role of wealth in individual career choices and lifetime earnings. Wealth provides a buffer for unexpected wage shocks that result from task-skill mismatch. Therefore, if workers' risk preference displays decreasing absolute risk aversion, those who have greater initial wealth are willing to endure more risk in order to find a better match, and they are more likely to find an occupation that fits their skills. Hence, wealth inequality could expand as a result of individual career choices even if every worker makes an optimal choice given their asset levels and their belief of about their skills.

I used the model to quantify the inefficient resulted from the informational friction and risk preferences by the initial wealth levels and to simulated the effects of recently proposed Baby Bonds policy on alleviating income inequality over the life-cycle.

To show the importance of ability learning, moreover, I use wage deviation as a productivity signal, and I show reduced-form evidence that workers adjust their occupations towards their comparative advantages as they learn about their skills. Better knowledge about workers' own ability will increase aggregate productivity through optimal sorting into skill-appropriate occupations. For future work, this structural model can be applied to evaluate policy impacts on the labor market, with respect to how these policies enhance occupation-worker skill match, training subsidies, and unemployment benefits.

A number of studies document that the social cost of occupational and sectoral mismatch is not negligible (Jovanovic and Moffitt (1990), Sullivan (2010), James (2011)). Self-selecting into a better occupational match, therefore, could be an important way to achieve more efficient allocation in the labor market. Also, important human capital investments, such as higher education or job training, often occur within a context of considering occupational decisions. Moreover, changing occupations often involves considerable variation in permanent income, which has a direct impact on household consumption and welfare. This structural model of occupational choice given imperfect information and risk aversion could, therefore, be useful in understanding occupational choices and other important economic behaviors within the same context.

Table 1.1: Summary Statistics

Variable	Mean	S.D.	N
Demographics and pre-labor market characteristics			
AFQT	49.0790	30.1438	2417
Years of Education	13.2375	2.5353	2417
Hispanic	0.1105	0.3135	2417
Black	0.0732	0.2506	2417
Age at the labor market entry	21.1386	2.9532	2417
Initial assets (log)	5.5706	2.6359	503
Wage and Occupations			
Hourly wage	17.6904	10.4820	31157
Cognitive task	0.5018	0.2645	32774
Motor task	0.5291	0.2487	32774

Notes: Summary statistics for 1 pre-labor market entry characteristics: AFQT score, years of educational attainment, race, age at labor market entry, and log of initial money assets, such as savings account, and 2) Labor market outcomes: hourly wage rate and task choices, using NLSY79 data from 1979-2000. Wages and assets are in 2005 real US dollars.

Table 1.2: Summary of Panel Data

	Hourly Wage			Cognitive Task			Motor Task		
t	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	N
1	11.8307	5.7708	2284	0.4124	0.2506	2412	0.5313	0.2268	2412
2	13.0147	6.3849	2293	0.4392	0.2579	2413	0.5334	0.2312	2413
3	13.6809	6.9410	2325	0.4532	0.2619	2410	0.5366	0.2378	2410
4	14.6976	7.7216	2218	0.4678	0.2630	2321	0.5342	0.2391	2321
5	15.4201	7.8133	2045	0.4741	0.2596	2138	0.5406	0.2450	2138
6	16.5760	8.7493	1915	0.5005	0.2633	1999	0.5424	0.2513	1999
7	17.5429	9.3701	1804	0.5069	0.2638	1885	0.5395	0.2495	1885
8	18.1036	9.6347	1732	0.5113	0.2646	1812	0.5356	0.2502	1812
9	18.8502	10.2204	1647	0.5260	0.2620	1732	0.5321	0.2561	1732
10	19.1571	10.3732	1592	0.5243	0.2668	1658	0.5214	0.2506	1658
11	19.8593	11.1129	1525	0.5339	0.2633	1597	0.5248	0.2586	1597
12	20.2770	11.2297	1452	0.5418	0.2650	1523	0.5126	0.2549	1523
13	20.5647	11.4465	1381	0.5380	0.2671	1455	0.5156	0.2560	1455
14	21.1374	12.0812	1297	0.5465	0.2627	1372	0.5124	0.2573	1372
15	22.0019	12.9901	1200	0.5417	0.2648	1264	0.5182	0.2575	1264
16	22.0607	13.2607	1069	0.5442	0.2585	1155	0.5231	0.2588	1155
17	22.0675	12.8598	928	0.5549	0.2523	1000	0.5294	0.2631	1000
18	22.1935	13.0519	781	0.5550	0.2544	834	0.5247	0.2626	834
19	23.3223	13.7584	641	0.5610	0.2543	694	0.5186	0.2594	694
20	23.0562	13.0674	460	0.5554	0.2525	488	0.5198	0.2582	488
21	23.0695	11.9703	323	0.5538	0.2566	353	0.5120	0.2588	353
22	23.4238	12.3660	245	0.5436	0.2525	259	0.5147	0.2596	259

Notes: The means and the standard deviations, along with the number of observations for hourly wage, cognitive task, and motor task for years after labor market entry (t) from the NLSY79 data (1979-2000). Wages are in 2005 real US dollars.

Table 1.3: Log Wage Regressions

	(1) OLS Log Wage	(2) FE Log Wage
$x_{c,t}$	0.818***	0.629***
	(0.0306)	(0.0279)
$x_{m,t}$	0.573***	0.431***
	(0.0379)	(0.0365)
$x_{c,t} \times x_{mt}$	-0.751***	-0.733***
	(0.0580)	(0.0579)
tenure_t	0.0759***	0.0723***
	(0.00333)	(0.00269)
tenure_t^2	-0.00307***	-0.00257***
	(0.000297)	(0.000244)
AFQT	0.00330***	
	(0.000132)	
education	0.0267***	
	(0.00157)	
hispanic	-0.0511***	
	(0.00978)	
black	0.0204*	
	(0.0105)	
constant	1.547***	2.229***
	(0.0280)	(0.0199)
N	31563	31563
adj. R^2	0.231	0.145

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $x_{c,t}$ and $x_{m,t}$ indicate the cognitive and motor tasks respectively. Tenure indicates occupational tenure. Education is measured by years.

Table 1.4: Career Transitions (OLS residuals)

	(1)	(2)
	$x_{c,t+1}$	$x_{m,t+1}$
$x_{c,t}$	0.720***	-0.108***
	(0.00731)	(0.00742)
$x_{m,t}$	-0.0714***	0.698***
	(0.00663)	(0.00673)
signal$_t$	0.0188***	0.0220***
	(0.00286)	(0.00290)
tenure$_t$	0.00530***	-0.00155
	(0.00137)	(0.00139)
tenure$_t^2$	-0.000291**	0.000225*
	(0.000128)	(0.000130)
signal$_t$ $\times$ $D_{c,t}$	0.0196***	-0.0425***
	(0.00443)	(0.00450)
$D_{c,t}$	-0.00142	0.0256***
	(0.00508)	(0.00516)
constant	0.179***	0.204***
	(0.00426)	(0.00432)
N	29309	29309
adj. R^2	0.548	0.480

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $x_{c,t}$ and $x_{m,t}$ indicate the cognitive and motor tasks respectively. Tenure indicates occupational tenure. Signal is the predicted residual from the OLS regression. Dummy variable $D_{c,t} = 1$ indicates $x_{c,t} > x_{m,t}$.

Table 1.5: Career Transitions (FE residuals)

	(1)	(2)
	$x_{c,t+1}$	$x_{m,t+1}$
$x_{c,t}$	0.716***	-0.110***
	(0.00730)	(0.00740)
$x_{m,t}$	-0.0675***	0.698***
	(0.00663)	(0.00672)
signal$_t$	0.0176***	0.0147***
	(0.00409)	(0.00414)
tenure$_t$	0.00528***	-0.00163
	(0.00137)	(0.00139)
tenure$_t^2$	-0.000290**	0.000226*
	(0.000128)	(0.000130)
signal$_t$ $\times$ $D_{c,t}$	0.0234***	-0.0556***
	(0.00623)	(0.00631)
$D_{c,t}$	0.00211	0.0258***
	(0.00508)	(0.00515)
constant	0.178***	0.205***
	(0.00426)	(0.00432)
N	29309	29309
adj. R^2	0.547	0.480

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $x_{c,t}$ and $x_{m,t}$ indicate the cognitive and motor tasks respectively. Tenure indicates occupational tenure. Signal is the predicted residual from the fixed effect regression. Dummy variable $D_{c,t} = 1$ indicates $x_{c,t} > x_{m,t}$.

Table 1.6: Wage and Risk Preference Parameters

	Cognitive Task	Motor Task
	Wage equation	
Intercept (B_0)	1.5772	
	(0.8876)	
Reward for task (B_{1c}, B_{1m})	14.5424	5.3875
	(4.8243)	(2.1358)
Cost for mismatch (B_{2c}, B_{2m})	28.5607	19.2269
	(1.8486)	(2.9714)
Interaction with skill (B_{3c}, B_{3m})	27.3512	20.6370
	(6.5409)	(3.1327)
Std. of wage shock (σ_ϵ)	0.5045	
	(0.2970)	
	Risk preference	
CRRA coefficient ρ	3.8666	
	(1.6216)	

Notes: Parameter estimates and standard errors (in brackets) for the wage and risk preference parameters. Wage parameters are the determinants for hourly wage rate, and risk preference parameter represents the estimates for coefficient of the CRRA utility function.

Table 1.7: Skill Accumulation and Initial Skills Parameters

	Cognitive Task	Motor Task
	Skill accumulation	
(A_{1c}, A_{1m})	0.0479	0.0663
	(0.0151)	(0.0286)
(A_{2c}, A_{2m})	0.0023	-0.0742
	(0.0132)	(0.0418)
Std. of skill accumulation shock (σ_η)	0.1081	0.0580
	(0.0299)	(0.0136)
	Initial skills	
Intercept (H_{0c}, H_{0m})	-1.2069	1.4885
	(0.4533)	(0.0851)
AFQT score (H_{1c}, H_{1m})	0.0027	-0.0012
	(0.0012)	(0.0011)
Years of education (H_{2c}, H_{2m})	0.1028	-0.0519
	(0.0256)	(0.0087)
Std. of initial skill shock ($\sigma_{\eta 0}$)	0.3616	0.2737
	(0.0868)	(0.0376)
	Initial belief	
Std. of initial belief distribution (σ_{s0})	0.3212	0.3866
	(0.0967)	(0.0954)

Notes: Parameter estimates and standard errors (in brackets) for skill accumulation and initial skill determination. Both deterministic and stochastic elements in skill accumulation and initial skills are separately estimated for each skill dimension, cognitive and motor.

Table 1.8: Life-Cycle Wage Profiles:
Skill Uncertainty vs. Perfect Information

	Low Wealth		High Wealth	
t	Uncertainty	Perfect Info.	Uncertainty	Perfect Info.
1	7.1563	9.5202	16.2367	17.5047
2	8.7742	9.8499	17.6144	18.2162
3	9.5224	10.2101	18.3133	18.8986
4	9.8739	10.5946	18.9814	19.6188
5	10.1794	10.9723	19.6510	20.3458
6	10.5170	11.3464	20.3811	21.1048
7	10.8772	11.7775	21.1224	21.9584
8	11.2332	12.1921	21.9257	22.7993
9	11.6360	12.6394	22.7999	23.6678
10	12.0277	13.0984	23.7412	24.5417
11	12.3827	13.5565	24.6485	25.4814
12	12.7948	14.0349	25.4134	26.3307
13	13.2324	14.5196	26.1842	27.1259
14	13.5978	15.0078	26.9423	28.0135
15	14.1359	15.5245	27.9774	28.9257
16	14.5943	16.0212	28.8376	29.7521
17	14.5462	16.5922	29.3503	30.3500
18	15.5865	17.1150	30.0801	30.9501
19	16.0646	17.6465	31.0962	31.7995
20	16.5295	18.2040	31.5660	31.8269

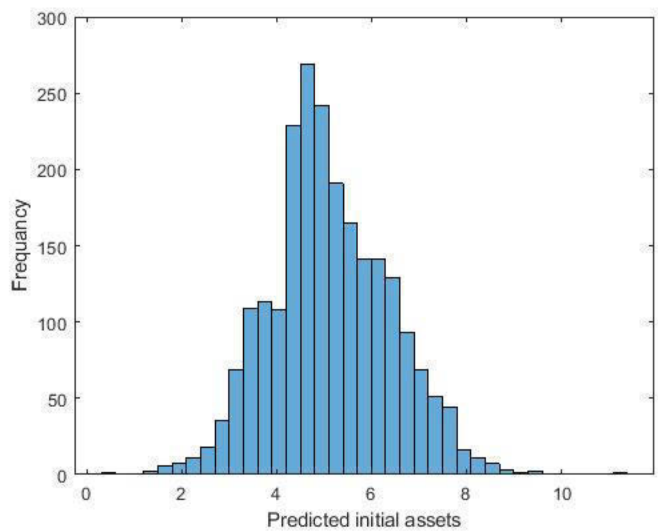
Notes: Hourly wage profiles for workers with and without skill uncertainty, by first-period wealth level. Low (high) wealth indicates that initial assets are lower (higher) than the median.

Table 1.9: Baby Bonds Simulation

Annual Income Ratio	Original Sample	Annual Supplemental Payment $1000	Annual Supplemental Payment $2000
Bottom 50%/ Top 50%	0.5131	0.5157	0.5319
Bottom 25%/ Top 25%	0.3495	0.3548	0.3819
Bottom 10%/ Top 10%	0.2466	0.2561	0.3002

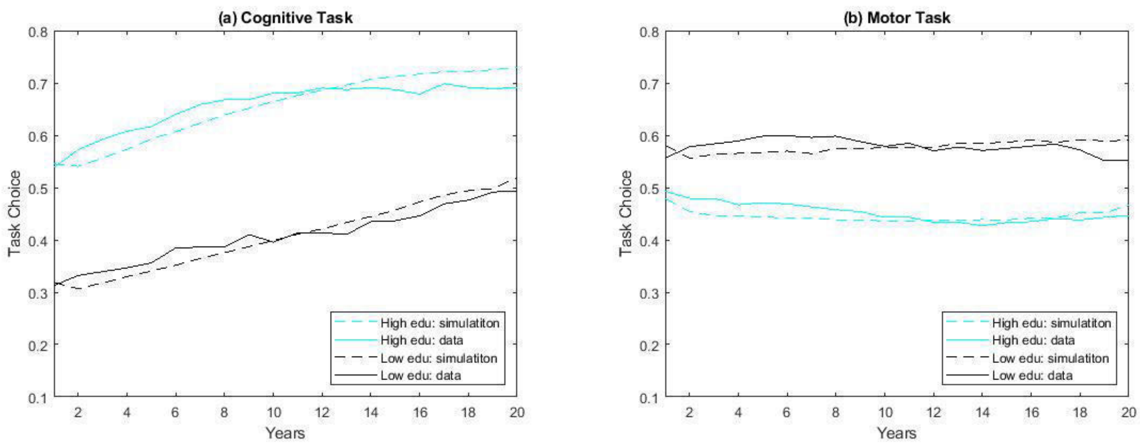
Notes: Simulation results for the effect of the proposed Baby Bonds policy on income inequalities over the life-cycle. Income ratios between average annual incomes by wealth groups are defined by 10%, 25%, and 50% of the first period of wealth distribution.

FIGURE 1.1: Predicted Log Initial Assets



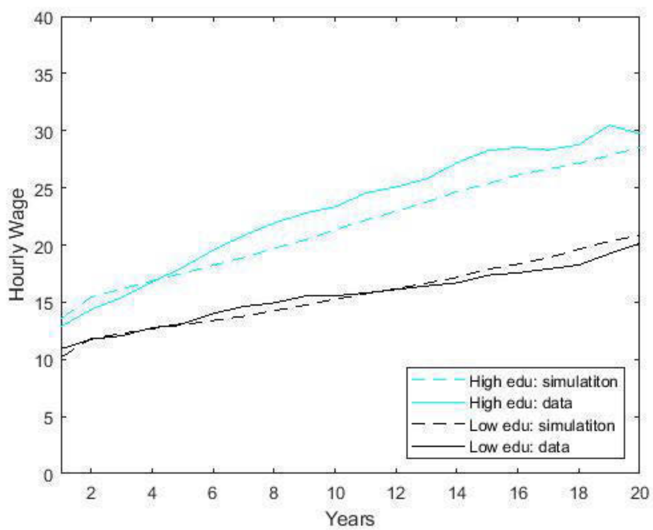
Notes: Predicted log initial assets at labor market entry. Predicted using the NLSY79 samples that have records of initial money asset holdings (such as a savings account), and years of education, AFQT score, first period wage rate and race.

Figure 1.2: Occupation Choice



Notes: Average occupation choice profiles by education level. Education is indicated as high if the final education level attained is some college or above; low if the final level is high school graduate or lower.

Figure 1.3: Hourly Wage



Notes: Average hourly wage rate profiles by education level. Education is indicated as high if the final education level attained is some college or above; low if the final level is high school graduate or lower.

Figure 1.4: Average Belief by Education Level

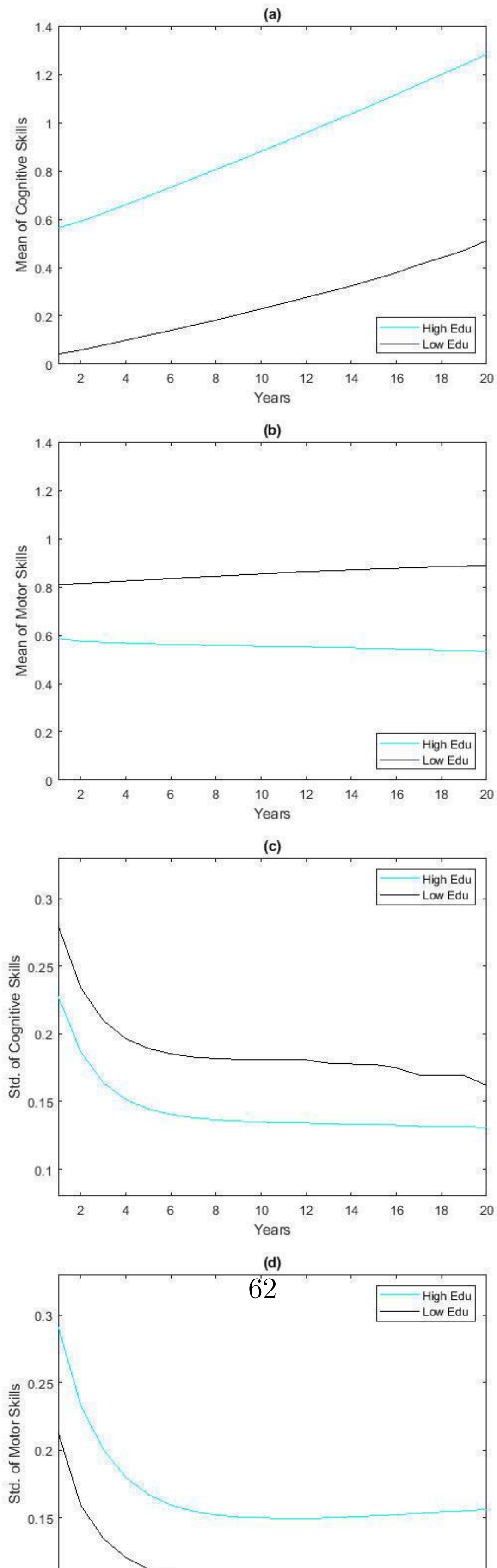
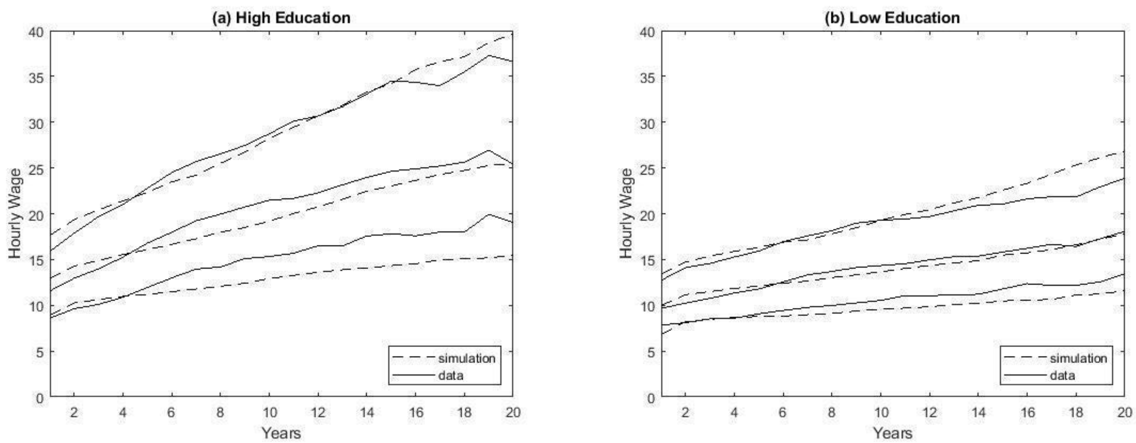
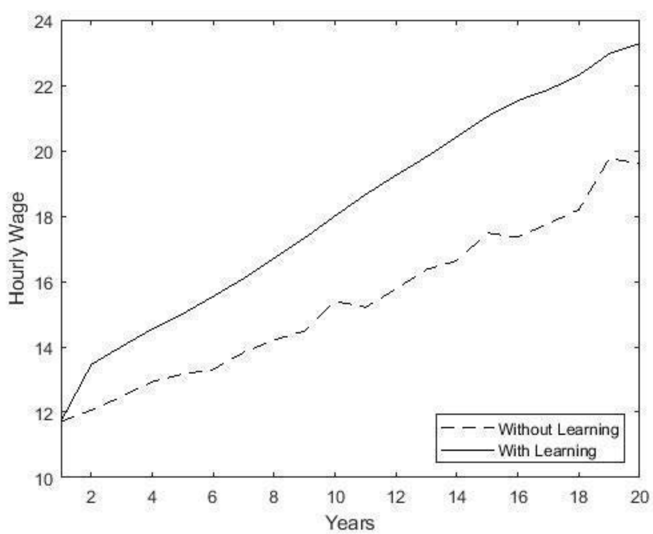


FIGURE 1.5: Wage Distribution: Interquartile Range and Median



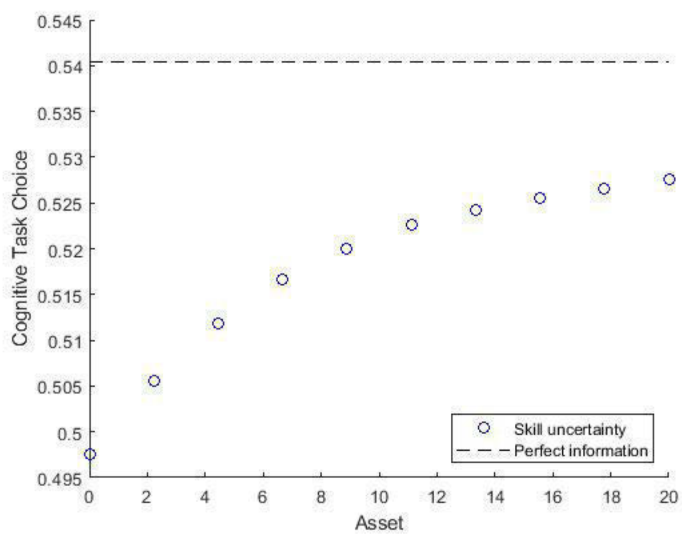
Notes: Hourly wage interquartiles and median, by education level. Education is indicated as high is the final education level attained is some college or above; low if the final level is high school graduate or lower.

FIGURE 1.6: Benefits of Learning



Notes: Dashed line indicates the average wage profiles for workers only with skill accumulation. Solid line represents the average wage profiles for the baseline model with both learning and skill accumulation effects. True skills and beliefs are fixed at the beginning of the life cycle.

Figure 1.7: Under-Investment in Occupational Choice



Notes: Dashed line indicates optimal cognitive task choices for a worker without skill uncertainty at each asset level; circles show optimal choices for an individual with skill uncertainty. True skills and beliefs are fixed at the population average, and assets are represented in the hourly dollar rate.

Chapter 2

Do Greater Unemployment Benefits Lead to Better Matches? Evidence from Emergency Unemployment Compensation Programs

2.1 Introduction

Budget-constrained job seekers may encounter serious consumption drops while unemployed (Gruber (1997), Browning and Crossley (2001)). Pressed by an urgent need for funds, they might be forced to take any available jobs, even if those jobs do not necessarily match their skills appropriately, with the subsequent result that such workers might experience lower productivity and earn less than what they could have earned if they were working on tasks more suitable their competitive advantages.

Past empirical research has found that UI benefits reduce the labor supply. (Moffitt (1985), Katz and Meyer (1990), Card and Levine (2000)). This trade-off between benefits and disincentives is central to the design of UI systems and to discussions about the generosity of UI benefits. A great number of studies have attempted to understand why UI benefits lengthen periods of unemployment, and there are two main explanations. The first hypothesis is moral hazard from a substitution effect; recipients of UI reduce their search efforts, as UI benefits can distort the relative costs of leisure and consumption (Krueger and Meyer (2002), Gruber (1997)). Second, in response to higher benefits, the reservation wage may go up, such that the probability of a UI recipient's accepting a new job offer diminishes (Ehrenberg and Oaxaca (1976)).

Alternatively, Chetty (2008) suggests that a substantial share of the response to longer UI benefits periods is attributable to a liquidity effect; UI allows liquidity-constrained households to spend as much time as they would have spent if they had enough funds for searching. In this way, UI benefits increase aggregate utility. Whether or not a job seeker's job-match quality positively correlates with the length of time spent searching is still an open question, with mixed evidence. Most existing empirical studies measure match quality using the post-unemployment wage or using tenure at the new job (Card et al. (2007), Chetty (2008), Van Ours and Vodopivec (2008)); however, while studies do find small-but-positive effects, others find none.

In this paper, I present new empirical evidence to suggest occupational choices as a channel by which unemployment insurance (UI) benefits might affect search behavior and result in longer unemployment durations. Recent literature on occupational tasks (Autor et al. (2003), Bacolod et al. (2009), Yamaguchi (2012), Autor and Dorn

(2013)) allowed researchers to evaluate a new dimension of occupational mobility: how occupations differ in terms of the types of job tasks they entail – that is, cognitive, manual, or routine skills. Using the occupational task data constructed by Autor and Dorn (2013), I show a positive correlation between changes in occupational tasks (i.e., from one task type to another or task levels) and unemployment durations. This evidence suggests that it takes longer to search and be matched with an occupation that requires skillsets or skill levels that differ from previous jobs. In turn, such a finding raises an interesting question: does additional wealth allow workers to take the risk of spending more time on their job searches, in order to find a better career match?

In this essay, thus, I report two findings that shed light on the positive relationship between additional wealth and the possibility of "experimentation" in the job search. Firstly, those with higher household wealth switch their job tasks more substantially than those with less wealth. I further measure a match quality with a previous job by pre-unemployment wage residuals, and find that, regardless of the level of household wealth, those whose previous occupation was a bad match are more likely to change their job tasks. Secondly, I show that an extension in the duration of UI benefits appears to induce occupational change.

My empirical strategy is closely related to Chetty (2008) and Kroft and Notowidigdo (2016), and I use cross-state variations in unemployment benefit durations during the early '90s. In 1991, the Extended Unemployment Compensation (EUC) program was established to increase the number of weeks of benefits during high-unemployment periods, to protect people who remain unemployed longer due to the greater difficulty in finding new jobs. As the additional benefit durations depended on state-level unemployment rates, UI durations varied across states. Although benefit levels and qualifications were revised five times during the EUC, one feature of the program that remained consistent was that these benefits were provided in two tiers through all periods. In addition, the unemployment rates during these periods were highly correlated across time. Therefore, I group the states into two categories to create a treatment status, depending on whether a state received higher-tier benefits or not.

Given the cross-state variations in UI benefit durations, then, I use data from the Survey of Income and Program Participation (SIPP) panels of 1990-1994, which cover dates before and after the EUC program's inception in late-1991. I estimate the average treatment effects of receiving UI benefits for longer durations, using the Difference in Differences and Matching methods. Using the Difference in Differences method, I find that occupational changes are more likely to be observed in the states that qualify for higher-tier EUC after EUC is implemented, compared to states that do not qualify. I then estimate the average treatment effect using Matching methods; I exploit both Nearest Neighbor and Propensity Score matchings to test the effect of the EUC on occupational changes and find consistent results using both methods.

The findings in this paper are consistent with the results in Chetty (2008): namely, that increases in UI benefits have much larger effects on unemployment durations for liquidity-constrained individuals than for wealthier ones. If it is to be expected that an individual must spend a longer time searching for an occupation that has no (or little) connection to his or her prior experience, and if unemployed people utilize UI benefits to subsidize these extended periods of unemployment, then it follows that increases in UI benefits will have larger effects on search durations for people who are financially constrained.

Although a change in occupation does not, in itself, constitute direct evidence for an improvement in job suitability or in post-unemployment welfare, this finding still sheds light on the possibility that UI extensions might facilitate improvements in welfare. First of all, people who are able to extend their job search until finding a better match might experience wage growth in the long run. Like many previous studies, the current paper reports that there is little change in accepted wages when comparing an individual's wages from his/her the final year at the previous job compared to his/her wages in the first year at the new job. However, given that individuals who change their occupation might reasonably lack occupation-specific experience at the start of a new job, this lack of experience might account for their lower starting wages. Taking this possibility together with another finding in this paper – namely, that individuals whose previous jobs were a poor match are more likely to switch occupations – it is possible that workers are freer to seek jobs with a better fit when they have the option of leaning on the support of extended UI benefits. Second, by selecting new, more-suitable occupations, workers might experience improvements in welfare that are associated with non-pecuniary job preferences.

The paper proceeds as follows. Section 2 presents a short summary of the previous literature on UI and post-unemployment match quality. Section 3 introduces the datasets used for the empirical analysis. Section 4 examines the effects of EUC extensions on search outcomes, namely, wage growth and occupation. Then, in Section 5, I estimate average treatment effects of EUC extensions, using the Difference in Differences and Matching methods. Section 6 discusses the evidence for the positive relationship between occupational change and search duration, and Section 7 provides a sketch of an occupational search model for credit-constrained individuals. Lastly, Section 8 concludes.

2.2 Previous studies on post-unemployment match quality

Given the universal empirical findings on the positive relationship between the generosity of UI benefits and unemployment spells, there is little evidence to show that generous UI benefits actually result in improved post-unemployment match quality. In other words, it has thus far remained unclear whether UI is associated with wage gains or with longer job tenures upon re-employment.

In Ehrenberg and Oaxaca (1976), the authors analyze unemployment duration and wage gains, using samples of UI recipients and non-recipients. They estimate the effect of the UI replacement ratio, which is defined as the ratio of weekly UI benefits to the UI recipient's weekly earnings at his/her former job. Their results show that the UI replacement rate does not have a significant impact on post-employment wages, and these results have been viewed as evidence for moral hazard in UI programs, as well as evidence that UI might reduce recipients' job-search efforts. Similarly, using Continuous Wage and Benefit History data for Pennsylvania and Arizona, Classen (1977) estimates the effect of an increase in the weekly benefit amount on post-unemployment wages and does not find UI to have a statistically significant effect on accepted wages in the post-unemployment job.

Addison and Blackburn (2000), on the other hand, do find a small but statistically significant effect in support of post-unemployment wage gains for UI recipients (compared to non-recipients) using data from the Displaced Worker Surveys for 1988, 1990, and 1992. The authors note that their finding may be biased by virtue of their decision to compare the recipients with non-recipients, as a similar effect is not found when comparing recipients at different levels of benefits.

More recently, Lalive (2007) has studied the effects of small (13-week) and large (170-week) extensions of UI benefits in Austria. The author finds that the more time-generous benefit programs seem to lengthen unemployment durations; however, these do not affect post-unemployment match quality, as measured by re-employment wage gains.

Using data from Austria and Slovenia, respectively, two recent studies – Card et al. (2007) and Van Ours and Vodopivec (2008) – examine multiple aspects of match quality, such as post-unemployment job duration and the probability of finding a permanent rather than a temporary job, in addition to wage changes. However, again, these authors find UI benefits to have little or no effect on post-unemployment match quality.

The current paper adds to the previous literature by testing and identifying the effects of UI programs on a new aspect of post-unemployment job match: occupational change. Occupational change alone is not direct evidence for improvements in worker-job match quality. However, this new aspect of search behavior sheds light on potential welfare improvements, taken together with two other findings in this paper; first, workers who were found to be poorly matched with the previous job also tend to experience larger shifts in terms of job tasks, and secondly, additional wealth have positive impacts on occupational changes.

2.3 Data

2.3.1 Dictionary of Occupational Titles

Starting from Autor et al. (2003), a growing body of studies (Ingram and Neumann (2006), Bacolod et al. (2009), Yamaguchi (2012), Autor and Dorn (2013)) take a new approach to define occupations, using task data from the Dictionary of Occupational Titles (DOT) or from its successor, the Occupational Information Network (O*NET). DOT and O*NET contain detailed task information on 12,099 distinct occupations. Each occupation is evaluated with respect to 62 characteristics, such as aptitudes, temperaments, necessary training time, and physical demand. Ingram and Neumann (2006), Bacolod et al. (2009), and Yamaguchi (2012) categorize these job characteristics by assigning them to just one of two dimensions – cognitive or motor – and define each occupation by task intensity. By contrast, Autor et al. (2003) and Autor and Dorn (2013) consider three skill dimensions – abstract, manual, and routine

– in analyzing the allocation of tasks between labor and capital, due to technological changes in the labor market.

In this paper, I use the three continuous task measures (abstract, routine, and manual) established by Autor and Dorn (2013). The measures are constructed from the DOT and matched to their corresponding three-digit Census occupation classifications. They collapse the original five task measures of Autor et al. (2003) to three task aggregates. The abstract task measure is the average of two DOT variables: "direction control and planning" and "GED Math," which measure managerial, mathematical, and formal reasoning requirements. The routine task measure is the average of two DOT variables: "set limits, tolerances, and standards" and "finger dexterity." And the manual task measure corresponds to the DOT variable "eye-hand-foot coordination."

Table 2.1 indicates the average task intensities for five major occupation groups. Managerial and professional specialty occupations, on average, have the highest abstract task scores, while Precision production, craft, and repair occupations have the highest routine and manual task scores. The lowest abstract task score was for operators, fabricators, and laborers, and the lowest routine task score was observed in the service occupations. Finally, the lowest manual task score was found among technical, sales, and administrative support occupations.

An advantage of using task-based occupational definitions rather than traditional categorization methods is that task-based definitions allow for evaluating whether two distinct occupations are similar or not. In addition, continuous task measures carry a computational advantage. In this way, despite the fact that the tripartite dimensional scheme accounts for a very low objective number of job characteristics, these categories (in combination) still account for theoretically infinite types of work; thus, researchers can still work conveniently with a large number of occupations.

2.3.2 Extended Unemployment Compensation

In the United States, UI benefits are normally provided for 26 weeks under the federal Unemployment Compensation (UC) program established by the Social Security Act of 1935. The UC program is periodically extended by a permanent Extended Benefits (EB) program or by temporary programs during economic downturns to protect people who (during a downturn) remain unemployed longer-than-normal due to the (temporarily) greater difficulty in finding new jobs. The permanent EB program was enacted in 1970 and provides one-half of regular benefits up to a maximum of 13 weeks. This program can be activated in a specific state if its adjusted insured unemployment rate (AIUR)[1] for 13 weeks is 4% or higher and if the quarterly average is at least 20% higher than the average of the previous 2 years. Meanwhile, the EB program can be activated nationally when the national IUR is 4.5% or higher for at least 3 consecutive months.

A temporary program, the Emergency Unemployment Compensation (EUC) Act of 1991[2] was established to increase the duration of UI benefits during periods of

[1]The insured unemployment rate is defined as the average of continuing UC claims for 13 weeks, divided by the average number of individuals in UC-covered employment over the first 4 of the last 6 quarters.

[2]Source: Emergency Unemployment Compensation: the 1990's Experience, Revised Edition, U.S. Department of Labor Employment and Training Administration,VI Occasional Paper 99-4.

high unemployment. The EUC program was signed into law November 15, 1991, and paid benefits through April 30, 1994. The EUC was superseded the EB program. A state that triggered on to EB had to drop from it in order to qualify for EUC. Also, an individual's EUC entitlement was reduced by any EB received under the EUC program.

The EUC program was revised five times, creating a complex web of benefit durations and levels across states. During that time (i.e., its November 1991 inception through the end of April 1994), a total of $27.9 billion in benefits was paid to recipients, and 5 million individuals exhausted their EUC benefits. Benefit durations and benefit tiers depended on the legislation of the time, across the five different iterations of the program's terms and conditions, as well as on state-level unemployment rates. Although the benefit levels and qualifications were revised five times, benefits were provided in effectively just two tiers[3] throughout all periods. Figure 2.1 shows a summary of cross-state variations in total weeks of UI benefits available during EUC periods. Two graphs in panel A indicate the high and low tiers of UI benefits, and panel B shows the mean and standard deviations across states. The spread between the two tiers was typically 6-7 weeks, and both the means and the standard deviations across states increased drastically from late-1991 to early-1992, decreasing thereafter.

Table 2.2 shows the additional weeks of EUC benefits for each tier by legislation,

January 1999.

[3]The first legislation that was effective from November 17, 1991 to February 8, 1992 had three benefit tiers: 20, 13, and 6 weeks added to a recipient's regular unemployment compensations. However, all states were qualified and received either 20 or 13 additional weeks of unemployment benefits.

and the number of weeks benefits that each state received. Data on Puerto Rico and the Virgin Islands are not available. Furthermore, Maine, Vermont, Iowa, North Dakota, South Dakota, Alaska, Idaho, Montana, and Wyoming are excluded, as SIPP does not provide unique state identifiers. The table, thus, includes the 14 states that qualified for Tier 2 benefits for at least one week during the legislative periods, while the remaining 27 states remained always in Tier 1. We can see that most states were in Tier 2 during the fourth and fifth legislative periods. For this reason, I focus only on the first three legislative periods, from November 17, 1991 to March 5, 1993.

Given the complexity of temporary UI laws during this period and the inadequate information on the date of UI claims, it is difficult to predict each individual's benefit level precisely. Therefore, I group the states into two categories, depending on the benefit tier in which each state found itself during the first three legislative periods, in order to construct a treatment variable. However, since the benefit level was able to change at any time depending on the state's unemployment rates, 12 out of 41 states are 'misclassified' for some weeks. The last column of Table 2.2 indicates the number of weeks deviated from Tier 2 from November 17, 1991 to March 5, 1993, where the deviation is 0 if a state was in Tier 2 the entire time and 68 if it was in Tier 1 the entire time. I use two measures of the treatment status, τ_b and τ_s, where $\tau_b = 1$ if the number of weeks deviated from Tier 2 is less than 34 weeks, and $\tau_s = 1$ if less than 20 weeks.

The two dummy variables τ_b and τ_s are time-invariant. However, as Table 2.2 shows, the number of potential weeks by state often changes over different periods.

Therefore, in addition to the two treatment status variables, τ_b and τ_s, I also test allowing the impacts of the EUC to vary by legislation period. For unemployment spells that stretch continuously across multiple periods, I assume the potential weeks to be based on the beginning of their unemployment spells.

2.3.3 Survey of Income and Program Participation

The ideal unemployment data for this paper are panels that include individual records of pre- and post-unemployment periods, as before-and-after comparison allows for a true measure of occupational change. Also, data on the availability of household assets are crucial in determining the effects that wealth might have on occupational change. At the same time, the ideal dataset should be time-expansive enough to contain observations both pre- and post-dating the policy intervention. Considering all of these factors, I use data from the 1990, 1991, and 1992 panels of the Survey of Income and Program Participation (SIPP), starting from January 1990 to August 1994; this date range is possible because each SIPP panel entails household surveys that continue for 2-4 years from the starting date, at 4-month intervals. The SIPP data contain information on weekly employment status, UI benefit status, and household assets.

To measure search durations, I follow Chetty (2008). I use weekly employment status (ES) from the SIPP data. ES can take any one of the following values: 1. With a job this week; 2. With a job, absent without pay, no time on layoff this week; 3. With a job, absent without pay, spent time on payoff this week; 4. Looking for a job this week; 5. Without a job, not looking for a job, not on layoff. Following Chetty (2008), I also define the duration of job separation by summing the number of weeks that ES >=3, starting at the time of job separation (i.e., when a change in ES from 1 or 2 to 3, 4, or 5 first becomes apparent) and stopping when the individual finds a job that lasts for at least 4 weeks (i.e., respondent reports on 4 consecutive occasions that ES = 1 or 2). The search duration is defined as a period of active job search, summing the number of weeks that a respondent reports that ES = 4. In case the tenure on a new job is less than 1 month, the search duration is calculated by summing the number of weeks in which ES = 4, until the person finds another job that lasts for 4 weeks, and the number of weeks in between wherein ES = 1 or 2 is excluded.

I restrict the samples to prime-age males between the ages of 18 and 65 who have at least 3 months of work history and appear in a panel for at least 3 months. The unemployment start date is considered to be when a worker with at least 3 months of work history becomes separated from a job. I exclude those who experienced their first job separation after March 1993, in order to cover the first three of the five EUC legislations. I further restrict the sample to those who are matched with a new job within the sample periods, excluding those who were still unemployed by the end date of the panel in question. I also exclude anyone on temporary layoff. In the end, I include only those people who lost jobs on or before March 1993, and the unemployment spells go as late as August 1994. Some have multiple unemployment spells in the data and have multiple observations. The final sample consists of 4,502 unemployment spells, 3,709 individuals, and an average of 1.21 unemployment spells per person.

To focus on the first three EUC legislations, I select only people who lost jobs on or before March 1993, leaving 1,248 unemployment spells that starts separations after March 1993 truncated. We may observe search outcomes and total search durations only for those who are successfully matched with new jobs during the panels. Therefore, individuals with shorter search durations are more likely to be selected in the sample, resulting a right-censoring problem. To adjust for this selection bias, I use a two-step sample correction method developed by Heckman (1979).

Table 2.3 presents summary statistics for the SIPP samples used in this paper. Note that wage information is missing for some samples that have records for pre- and post-unemployemnt occupations. The average tasks before and after unemployment are similar to each other. Scores for abstract, routine, and manual tasks before job separation are 2.234, 4.34, and 1.7, respectively; in post-unemployment occupations, these are 2.221, 4.28, and 1.714, respectively. The average of the task scores across all 3-digit Census occupations are, respectively, 2.886, 4.627, and 1.308. Therefore, the unemployment SIPP samples have relatively lower abstract and routine tasks compared to the average across all occupations, while the SIPP is higher than the average on manual tasks.

The average ln wage is also similar before and after job separation. The average ln wage before unemployment is 5.520 for the whole samples, and 5.592 for those who have post-unemployment wage data, while the mean post-unemployment ln wage is

5.677.

2.4 Effects of UI on Post-Unemployment Wages and Occupations

As in the previous studies discussed in Section 2, I do not find any evidence to suggest that UI increases a job seeker's accepted wages after unemployment. As in Card et al. (2007), I define wage growth $h_i = ln(w_i^n) - ln(w_i^p)$ where w_i^n is individual i's wage in the first year at the post-unemployment job, and (w_i^p) is the wage in the final year at the previous job.

To evaluate effects of UI on post-unemployment wages, I use only samples after EUC is implemented to estimate the following OLS regression,

$$h_i = \mu_0 + \mu_1 \tau_i + \theta \tilde{X}_{it} + \epsilon_{it} \tag{2.1}$$

A treatment status $\tau_i = 1$ indicates the eligibility for the Tier 2 UI extension as defined in the previous section. Controls $\tilde{X}_{it}$ include search durations, age, age squared, years of education, a race dummy, and quartiles of household wealth distribution.

In addition, I test whether the UI benefit extension has affected occupational changes, using a similar specification, but replacing wage growth h_i to the distance between pre- and post-unemployment occupations, D_i. D_i is measured by the Euclidean distance in three-dimensional occupational tasks, according to Autor and Dorn (2013) 's categories: abstract, routine, and manual.

$$D_i = (T^p_{iA} - T^n_{iA})^2 + (T^p_{iR} - T^n_{iR})^2 + (T^p_{iM} - T^n_{iM})^2 \tag{2.2}$$

T^k_{iA}, T^k_{iR}, and T^k_{iM} are abstract, routine, and manual task intensities, respectively, and k indicates pre- $(k = n)$ and post- $(k = p)$ unemployment. Therefore, D_i measures how different the new occupation is compared to the previous job.

Tables 2.4 and 2.5 present summary statistics of covariates by the treatment statuses τ_b and τ_s and their differences. Both wage and occupational distance are higher in the treated group, and the difference is bigger between $\tau_s = 1$ and $\tau_s = 0$ compared to the difference between $\tau_b = 1$ and $\tau_b = 0$. Similar trend is found in search duration (weeks) and net liquid household assets. Black respondents make up about 10% of the whole sample, and the population is slightly larger in the control groups. The three job task measures, as well as age and years of education, are not significantly different between the two groups.

The regression results in Table 2.6 are also consistent with the findings in existing studies on the effects of UI on accepted wages. Table 2.6 examines the effects of treatment status τ, the eligibility for the longer UI extensions. Columns (1) and (3) include only age and its squared term as controls, and Columns (2) and (4) add the full control set, including education, a race dummy, household wealth distribution quartiles, and search durations. Regardless of how the treatment group is defined, for both τ_b and τ_s, a respondent's eligibility for the longer UI extensions does not have a statistically significant effect on his post-unemployment wage growth, h_i. The coefficients of the treatment status for all four regressions are positive, but close to 0 and not significant. Search durations do not have any significant effect on wage growth either, as shown in columns (2) and (4).

Estimation results in Table 2.7 show that the treatment status τ, however, affects post-unemployment occupational choices. Changes in occupational task, D_i increase with eligibility for longer UI extensions. Both treatment status τ_b and τ_s have similar levels of coefficients without additional controls, 1.848 and 1.949, respectively. With full controls, then, the coefficients on τ_b and τ_s are 1.150 and 1.658, respectively, and the τ_b coefficient is not statistically significant. Search durations – that is, weeks of unemployment while searching for a job – are also positively related to occupational change, as shown in Columns (2) and (4). Therefore, those who spend longer searching for a job are more likely to switch occupational tasks when reemployed.

Although an immediate improvement in wages is not evident, occupational changes as a response to UI benefit extensions do imply that not all behavioral responses to more generous UI benefits are explained by moral hazard; when they can avail themselves of more funds during the search period, it seems that workers may expand their searches to include new occupations with which they have no previous experience. This explanation is consistent with the findings in Chetty (2008) that increases in UI benefits have much larger effects on unemployment durations for liquidity-constrained individuals. If it is to be expected that searching for a new occupation will require more time than searching for a more familiar one, and if unemployed people utilize UI benefits to subsidize extended periods of unemployment while they find a new job, then increases in UI benefits should have larger effects on search duration when people are credit-constrained.

In the following section, I will explore the effects of UI extensions on occupational change in more detail, using the Difference in Differences and Matching methods.

2.5 Average Treatment Effects of UI on Occupational Changes

2.5.1 Difference in Differences Analysis

The outcome of interest is the distance between the observed pre- and post-unemployment occupations, D_i. Using a treatment status $\tau_i = 1$, eligibility for Tier 1 UI extension, I first analyze the average treatment effect of EUC on occupational change by the conventional DID approach. $T = 0$ indicates pre-EUC spells that began before November 1991, even if a given spell ended after November 1991, and $T = 1$ indicates post-EUC spells that began in or after November 1991.

Table 2.8 shows the average occupational distance by treatment status for pre- and post-spells. We can see that the occupational distance is greater in the treatment group on average. Moreover, it increases after EUC in the treatment group, while it decreases after EUC in the control group. Difference in difference is higher for $\tau_s = 1$ than $\tau_b = 1$.

$$D_{it} = \beta_0 + \beta_1 g_i + \beta_2^j Q_{ij} + \beta_3 \mathbf{1}_T + \beta_4 \mathbf{1}_\tau + \beta_5 \mathbf{1}_T \mathbf{1}_\tau + \gamma X_{it} + \epsilon_{it}. \tag{2.3}$$

Q_{ij} is an indicator variable that $=1$ if individual i belongs to quartile j of the wealth distribution. And $\mathbf{1}_T = 1$ indicates a time period after the treatment event. Control X_{it} includes current occupational task levels, age. To interpret β_5 as an average treatment effect of EUC, it is required that the average outcomes for the treated and control groups would have followed parallel paths over time in the absence of the treatment. Finally, g_i denotes the wage signal for individual i derived from the following ln wage regression.

$$ln \text{ wage}_{it} = \alpha_{0t} + \alpha_1 \text{task} + \alpha_2 \text{task}^2 + \gamma' X'_{it} + \mu_i + \delta_t \eta_{it}, \tag{2.4}$$

where X'_{it} includes educational attainment, race dummies, age, and age squared. μ_i represents state fixed effects, and δ_t represents year fixed effects. Wage signal g_i is the residual from the ln wage equation (2.4). Therefore, g_i, which is the excessive wages from the previous occupation, is used as a proxy for the match quality from the previous job. Workers make occupational choices based on their past experience. In particular, workers can change occupations to insure themselves against earnings risks attributable to a poor match with job tasks. Workers whose previous occupations were a bad match might adapt themselves to different kinds of tasks, and those who are well matched in their current occupations would likely stay with similar occupations (in terms of job tasks) going forward.

2.5.2 Truncated Distribution and Correction for Sample Selection Bias

The dependent variable distance D_i is observed only if an individual is successfully matched with a new job within the panel in question, resulting in a right-censoring problem. Individuals with shorter unemployment spells are more likely to be included in the sample. To adjust for this selection bias, I use the two-step sample correction method developed by Heckman (1979).

The occupational distance D_i is observed only if

$$\gamma_0 + \gamma_1 n_i + \gamma_2 \tilde{X}_i + \mu_i + u_i > 0. \tag{2.5}$$

n_i indicates the year and month when individual i is separated from a job. n_i is a monthly time variable, starting from January 1990 where $n_i = 1$ to March 1993 where $n_i = 39$. The later that an individual lost his job, it would be more likely that he was not ultimately matched successfully with a new job and thus was omitted from the data. $\tilde{X}_{it}$ includes search durations, age, age squared, years of education, race dummy, and quartiles of household wealth distribution, while μ_i represents state fixed effects.

Table 2.9 shows estimates from the Probit regression in equation (2.5). Calendar year and month at job losses and the current search durations are negatively related to the sample selection. On the other hand, older people and people who engaged more in (as represented by higher scores on) abstract tasks in their previous job are more likely to find a job before the panel ends and are included in the sample. From selection equation (2.5), I construct the non-selection hazard, or the inverse of Mill's ratio $lambda_i = \frac{\theta(Z_i)}{1-\Theta(Z_i)}$, where Z_i is the predicted selection probability.

2.5.3 Results

Table 2.10 shows the classic difference in differences estimation result. Specification (1) does not include the non-selection hazard, *lambda*, while Specifications (2), (3), and (4) include it to correct the selection bias caused by the truncated distribution of occupational distance. In addition to *lambda*, Specification (3) includes dummies for each legislation period for EUC, and Specification (4) includes legislation period dummies and their interactions with EUC status in each state for that period. For some states that changed their EUC status within a given period, I assigned 1 if the state was in the higher tier for the majority of that time; otherwise I assigned 0.

For all four specifications, the average treatment effect of EUC is positive and statistically significant, and the estimates are higher for tau_s than tau_b. The coefficient is larger and more significant with the controls for legislation period dummies $p1, p2$ their interactions with EUC status in each state for that period. The negative time specific effect was strongest during the first legislation period, which is in the beginning of the recession. And the effect of EUC weakest in the last period of legislation, p.

Regardless of the treatment status, household assets play an important role in occupational task changes. Q_j is an indicator variable for the jth quartile of the wealth distribution. Those who are in the 3rd and 4th quartiles are more likely to switch their jobs more drastically compared to the people in the 1st and 2nd quartiles. There are two possible explanations for this finding. The first explanation centers on the fact that unemployment search duration is highly correlated with occupational change; the data show that the bigger a change is, the longer it has likely taken a worker to be successfully matched with his new job – and we can surmise that only those who are not liquidity-constrained can afford to wait through longer searches. The finding here supports Chetty (2008)'s findings that the effect of unemployment benefit extension on search duration is much larger for workers with low household liquidity. The second explanation is consistent with the positive relationship between wealth and optimal levels of occupational risk taking, as addressed in Bahk (2020). If workers are uncertain about their skill levels, then choosing occupations that require very different (combinations of) occupational tasks is risky, since a worker's productivity and potential earnings in the new occupation would be unknown; as such, only those workers with greater wealth might be able to take on the bigger risks associated with changing one's occupation substantially.

Another key variable in Table 2.10 is the signal from equation (2.4). The negative coefficients on the signal suggest that workers with low productivity signals from their previous job are more likely to make bigger changes in occupational tasks, and those with good signals are matched again with rather similar occupations after unemployment. The estimates are similar in all specifications and range from -1.523 to -1.566. This result is consistent with the findings in Arcidiacono et al. (2016) that workers with positive wage residuals are more likely to stay in the same occupation.

Wage regression results, as well as the estimates exploited to derive the signals, are presented in Table 2.11.

Also, the occupational changes drop significantly with age, which is consistent with the classic findings in the search and matching literatures that occupational change is particularly active in the beginning of a worker's career. Meanwhile, although unemployment rates have strongly negative correlations with search durations, they do not have a significant impact on occupational change.

2.5.4 Matching Methods

Methods and Results

One of the key benefits of randomized experiments in estimating causal effects is that both observed and unobserved covariates in the treated group are only randomly different from the control group. Unfortunately, in many non-experimental studies, the status of having received a treatment is not always independent of the treated units' characteristics; in such cases, if the treated units' outcomes are at least partly determined by some of these factors, the treatment process itself may result in selection bias (Rubin (1973), Heckman et al. (1998)). Therefore, when estimating causal effects in non-experimental studies, it is desirable to reduce bias as much as possible by obtaining well-matched treated and control groups with similar covariates.

As shown in Tables 2.4 and 2.5, which present summary statistics of covariates in treated and control groups and their differences, a simple comparison suggests that there is a room to improve the balance between the two groups. For both broad (τ_b) and narrow (τ_s) distinctions, there are significant discrepancies in the distributions, although the differences are bigger in the narrow treatment group. *ln* wage, signal, and occupational distance are slightly higher in the treated group, as well as household net liquid assets. Job task measures, years of education, and age are not significantly different between the two groups.

Matching methods (Althauser and Rubin (1970), Rubin (1973)) are based on the idea of balancing the distribution of covariates in the treated and control groups to compare the outcomes of subjects that are as similar as possible with the single exception of their treatment status. Matching methods include matching in covariates (Abadie and Imbens (2002)), and methods based on propensity score (Rosenbaum and Rubin (1984), Hirano et al. (2003)). In this paper, I use both nearest neighbor matching and propensity score matching to compare similar units between the treatment and control group.

Nearest neighbor matching entails finding the closest pairs of observations with regard to a set of covariates.

$$\hat{D}_i(0) = \begin{cases} D_i & \text{if } \tau_i = 0 \\ \bar{D}_{l(i)} & \text{if } \tau_i = 1 \end{cases} \tag{2.6}$$

$$\hat{D}_i(1) = \begin{cases} \bar{D}_{l(i)} & \text{if } \tau_i = 0 \\ D_i & \text{if } \tau_i = 1 \end{cases} \tag{2.7}$$

$\bar{D}_{l(i)}$ indicates the average of Mth closest units (in terms of covariates X_i) in the opposite treatment group, where M is the number of matches. Then the simple matching estimator in Abadie and Imbens (2002) is

$$\Gamma^{sm} = \frac{1}{N}\sum_{i=1}^{N}(\hat{D}_i(1) - \hat{D}_i(0)). \tag{2.8}$$

However, unless the covariates are exactly matched, there may still be bias due to the difference in the covariates, even though the difference is smaller after matching. Regardless, to account for this possible bias, I adjust using a linear function of covariates as suggested in Abadie and Imbens (2002).

Propensity score matching is an alternative to the nearest neighbor matching method. Instead of correcting the bias that may arise in cases where all covariates are not exactly matched, propensity score matching matches on the estimated predicted probabilities of treatment, also known as the propensity scores. The propensity score naturally includes all information about the covariates and can perform as a single covariate for use in matching.

Table 2.12 shows the matching estimators. The matched covariates comprise the three task-type measures, a wage signal g_{it} from the pre-unemployment job (equation (2.3)), household net liquidity quartiles, age, race, and years of education. Since the available sample includes numbers of controls and the treated, I used a single match in the estimation. Selecting multiple matches generally increases bias, since the second or next-closest controls are further away from the treated unit than is the absolute closest match. However, when the sample size is small, utilizing multiple matches can decrease variance by increasing the matched sample size. For both treatment groups, the matching estimators for the average treatment effect are significantly positive, ranging from 1.284 to 1.855.

Discussions for Unconfoundedness and Overlap assumptions

There are two assumptions critical to identifying the treatment impact using matching methods. The first assumption is "unconfoundedness" which is also referred to as exogeneity (or the conditional independence assumption), formally articulated in Rubin (1990),

$$\tau_i \perp (D_i(0), D_i(1)) \ | X_i. \tag{2.9}$$

Conditional on the covariates X_i, the outcomes δ_i are independent with the treatment status τ_i. Unconfoundedness is an important condition when estimating casual effects using observational data, which assures that the assignment to treatment is based on observational pre-treatment variables only. In many non-experimental studies, assessing the plausibility of the unconfoundedness assumption can be a challenge. In this study, the assignment rule for $\tau_i = 1$ is clear: it depends on a single variable, which is the state's unemployment rate. However, there may exist unobserved systematic differences in the covariates that affect occupational changes and this unemployment rate, hence the treatment and control status.

The unconfoundedness assumption is not testable, since only one of the outcomes for each treatment status is observable. However, researchers can assess the plausibility of this assumption by estimating the causal effect of the treatment on a pseudo-outcome, which is a variable known to be unaffected by the treatment. I use the samples before the treatment status; therefore, the value is determined prior to the treatment, to perform (otherwise-identical) matching estimations. Table 2.13 reports that for all four specifications, the matching estimators are insignificant and close to 0, showing that the unconfoundedness assumption is plausible.

The second assumption is overlap. The overlap assumption states that each individual has a positive probability of receiving the treatment. Formally, the overlap assumption requires that for each possible X in the population,

$$0 < \Pr(\tau = 1|X) < 1. \tag{2.10}$$

where $\Pr(\tau = 1|X)$ is a propensity score. The overlap assumption is satisfied when there is a positive probability of seeing observations in both the treatment and the control group given each combination of covariates. Figure 2.2 shows the two estimated densities of the predicted probabilities of being treated using the covariates X. Both plots have its mass in the middle, not near 0 or 1, and there is a sufficient overlap between the two groups. Therefore it is plausible to say that the overlap assumption is not violated.

2.6 Search Durations and Changes in Occupation

In this section, I provide evidence for a positive relationship between occupational changes and search durations using a simple OLS regression. There are various kinds of potential risk involved in choosing a new job that entails different kinds of job tasks. A model of task-specific job searching (Bahk (2020)) shows that job seekers with higher household assets tend to move further in terms of (change in) occupational tasks. At the same time, a positive relationship between occupational changes and search durations suggests another potential risk when changing occupations; it may take longer to search for jobs outside of one's field of experience.

$$\text{search durations}_i = \zeta_0 + \zeta_1 D_i + \zeta_2 w_i + \zeta_3 g_i + \gamma' X_i' + \nu_i \tag{2.11}$$

Table 2.14 shows estimation results for the OLS regression (equation (2.9)), where X_i includes state unemployment rates, year-specific effects, and individual characteristics, such as age, years of education, race, and household liquidity asset levels. Search durations are measured as the weeks of unemployment periods people have reported that they are actively searching for a job.

Search durations are likely extended with higher unemployment rates. Also as people age, it is likely that finding a new job will take them longer. Household net liquidity assets, on the other hand, do not seem to have a significant impact on job search durations. While productivity signals from a respondent's previous job are negatively correlated with search duration, this relationship might relate to unobserved characteristics, such as search efforts or innate ability – or it may be partly attributable to the fact that people with low wage signals from their previous jobs are more like to choose a different sort of job, involving different tasks. Interestingly, then, when controlling for the productivity signal, higher wages at the previous job are positively correlated with unemployment duration. Lastly, search duration and occupational change show a positive and significant relationship.

2.7 An Occupational Search Model

In this section, I sketch a simple occupational search model. This model builds on Card et al. (2007) and on Chetty (2008), who developed job search models with a borrowing constraint. One major difference from the search models is that the agents choose occupational distance (i.e., the magnitude of the change in occupational task types) d_t when they become unemployed, instead of search efforts. In addition, utility when employed depends on the match quality with a new occupation. I make the following two assumptions for simplicity: first, I assume that all jobs last indefinitely once matched, and second, I assume that wages are exogenously fixed.

Time is discrete in a finite horizon. Agents become unemployed at $t = 0$. An agent chooses occupational distance $d_t \in [0, \bar{d}]$. If $d_t = 0$, then the occupation is same as in the previous job. Distance d_t affects the probability of a successful match,

$p(d_t)$, which I assume $p'(d_t) < 0$. Therefore, as d_t increases, the agent is less likely to be matched with a new job. δ denotes a time discount rate, and r is the fixed interest rate. $m(d_t, g)$ denotes match quality in the new job, where the match quality is determined by the productivity signal from the previous occupation g and by the distance d_t. If the search is successful, the agent begins working and receive wage w_t until the end of the periods. If the agent fails to find a job in period t, the agent receives an unemployment benefit b_t and searches again in period $t + 1$.

The value function for an agent who are matched with a job in period t, given the assets A_t is

$$V_t(A_t) = \max_{A_{t+1} \geq L} u(A_t - \frac{A_{t+1}}{(1+r)} + w_t) + m(d_t, g) + \frac{1}{1+\delta} V_{t+1}(A_{t+1}), \tag{2.12}$$

where L is a lower bound on assets. The value function for an agent who fails to find a job is

$$U_t(A_t) = \max_{A_{t+1} \geq L} u(A_t - \frac{A_{t+1}}{(1+r)} + b_t) + \frac{1}{1+\delta}, J_{t+1}(A_{t+1}), \tag{2.13}$$

where

$$J_t(A_t) = \max_{d_t} p(d_t) V_t(A_t) + (1 - p(d_t)) U_t(A_t). \tag{2.14}$$

An unemployed individual chooses d_t to maximize expected utility given by equation (2.13). Given the level of assets A_t and the productivity signal g from the previous occupation, the first order condition that the optimal distance $d_t^* \in (0, \bar{b})$ is

$$p'(d_t^*)(V_t(A_t) - U(A_t) + p(d_t^*)\frac{\partial m(d_t^*, g)}{\partial d_t^*} = 0, \tag{2.15}$$

and the optimal distance $d_t^* = 0$ if $\frac{\partial m(d_t, g)}{(\partial d_t)} \leq 0$ given g.

The optimal occupational distance is determined by the productivity signal g. Intuitively, an unemployed individual who was well matched at his previous occupation would be better off looking for the same job tasks or even the same exact occupation. However, if the match quality was very low, the agent might choose $d_t > 0$ in order to increase his match quality at his next job, even if the probability of a successful match (in such a case) is lower.

2.8 Conclusion

In this paper, I suggest and test occupational choices as a new channel between UI benefits and longer unemployment durations. Using cross-state variations in weeks of UI benefits available in the early 1990s, I find that unemployed individuals with higher levels of wealth search for different kinds of jobs with different task levels than do individuals with lower levels of wealth. Also, using different levels of EUC extensions as a treatment status, I find similar behavioral responses to UI benefits extensions, as though these benefits function as a stand-in for wealth. I control for previous occupation and previous job's match quality, and I find that people tend to "experiment" and move further away from their previous occupations when they are supported by UI for longer periods.

The occupational choices of the unemployed offer insight into a "new" possible facet of the value of UI, one that has previously not received enough attention. In particular, the fact that people whose previous jobs were a poor match are more like to change their occupational tasks when they have greater household assets or more generous UI benefits highlights some potential welfare improvements for credit-constrained workers. However, occupational change itself dose not provide direct information about workers' post-unemployment welfare, such as post-unemployment occupational tenure, match quality at these new jobs, or the question of whether workers are more satisfied with their new occupations.

Assessing the value of the occupational changes facilitated by UI can be a future avenue of research. One potential reason why post-unemployment wage levels are not affected by UI extensions in this study – while occupational choices are – is because of how the current study has defined wage growth. Wage growth is measured by the difference between wages during the final year in the previous occupation and wages during the first year in the new one. Even if individuals find a better occupational match by changing job tasks, the monetary payoffs may not be immediate when they change job tasks completely, because they may yet lack valuable task-specific experience.

Moreover, observations on occupational choice across a longer span of time might afford a better understanding of post-unemployment occupational tenure. Using the task-based occupation data, with the measure for the direction of occupational movement in hand, we can evaluate how an individual's professional focus – as measured by job task type – is evolving over time.

In both cases, long-panel data would allow researchers to ascertain whether there were any long-term benefit to task changes. These, and any further evaluations for post-unemployment welfare in a context of occupational change, are left for future studies.

Table 2.1: Average Task Intensity of Major Occupation Groups

	Abstract	Routine	Manual
Managerial and professional specialty	5.558	3.682	0.980
Technical, sales, and administrative support	2.559	4.801	0.506
Service	1.629	2.803	1.512
Precision production, craft, and repair	1.955	6.655	1.879
Operators, fabricators, and laborers	1.165	4.792	1.788

Table 2.2: Treatment Status and EUC Benefit Durations (Weeks) by State and Law

	11/17/91 P.L.102-182	2/8/92 P.L. 102-244	6/14/92 P.L.102-318	3/6/93 P.L.103-6	10/2/93 P.L.103-152	Dev. from Tier 2
Tier 1	13	26	20	10	7	
Tier 2	20	33	26	15	13	
Arkansas	13 20(2/2/92)	33	20	10	7	49
California	13 20(1/5/92)	33	26	15	13	7
Connecticut	20	33	26 20(11/1/92)	10	7	18
Massachusetts	20	33	26 20(8/2/92)	10	7	31
Michigan	20	33	26 20(10/25/92)	10	7	19
Mississippi	20	33 26(2/16/92)	20	10	7	51
Nevada	13	26 33(3/8/92) 26(6/6/92)	20	10	7	55
New Jersey	20	33	26 20(11/22/92)	10 15(3/7/93) 10(6/13/93)	7	15
New York	13	26 33(2/16/92)	26 20(7/12/92)	10	7	47
Oregon	13 20(1/12/92)	33	26 20(9/27/92) 26(1/31/93)	15 10(7/11/92)	7 13(2/26/94)	26
Pennsylvania	13 20(1/26/92)	33	26 20(8/16/92)	10 15(3/21/93) 10(6/20/93)	7	39
Rhode Island	20	33	26	15	7 13(1/16/94)	0
Washington	13 20(2/2/92)	33	26 20(7/4/92)	15 10(6/27/93)	7	41
West Virginia	20	33	26	15	13	0

Source: Emergency Unemployment Compensation: the 1990's Experience, Revised Edition, U.S. Department of Labor Employment and Training Administration,VI Occasional Paper 99-4. January 1999. Data on Puerto Rico and Virgin Islands are not available. Maine, Vermont, Iowa, North Dakota, South Dakota, Alaska, Idaho, Montana, Wyoming are excluded as SIPP does not provide unique state identifiers.

Table 2.3: Summary Statistics

	Mean	S.D.	Observations
Worker Characteristics			
Age	32.089	10.806	4,627
Education	12.264	2.737	4,627
Black	0.109	0.312	4,627
Net liquid assets	17280.31	72502.38	4,627
Pre-unemployment			
ln wage	5.520	0.854	4,502
Abstract task	2.334	2.063	4,627
Routine task	4.340	2.238	4,627
Manual task	1.700	1.474	4,627
Post-layoff			
Search duration	13.857	13.424	4,627
ln wage	5.677	0.764	3,452
Abstract task	2.221	1.979	4,627
Routine task	4.280	2.236	4,627
Manual task	1.714	1.477	4,627

Table 2.4: Summary Statistics by Treatment Status τ_b

	$\tau_b = 0$		$\tau_b = 1$			
	Mean	S.D.	Mean	S.D.	Difference	t-stat
ln wage	5.488	0.839	5.584	0.881	-0.096	-3.525
Distance	10.491	14.842	11.390	16.149	-0.899	-1.852
Age	32.235	10.895	31.722	10.617	0.513	1.495
Education	12.244	2.685	12.300	2.865	-0.055	-0.226
Black	0.128	0.334	0.071	0.256	0.057	5.821
Search duration	13.003	12.540	15.202	14.208	-2.198	-5.279
Net liquid assets	13,293	55,484	26,149	99,658	-12,856	-5.549
Abstract task	2.325	2.044	2.388	2.131	-0.063	-0.961
Routine task	4.336	2.226	4.290	2.265	0.046	0.649
Manual task	1.703	1.473	1.676	1.484	0.028	0.586
Unemployment rate	6.567	1.192	7.935	1.421	-1.368	-33.869
Signal	0.000	0.699	0.00	0.712	0.000	0.000
N	3,029		1,473			

Table 2.5: Summary Statistics by Treatment Status τ_s

	$\tau_s = 0$		$\tau_s = 1$			
	Mean	S.D.	Mean	S.D.	Difference	t-stat
ln wage	5.492	0.844	5.596	0.879	-0.104	-3.572
Distance	10.515	14.905	11.552	16.302	-1.037	-1.999
Age	32.079	10.852	32.036	10.678	0.043	0.117
Education	12.299	2.656	12.161	2.984	0.137	1.472
Black	0.121	0.327	0.075	0.264	0.046	4.372
Search duration	13.252	12.748	15.061	14.144	-1.809	-4.058
Net liquid assets	14,196	61,375	26,885	98,777	-12,689	-5.119
Abstract task	2.239	2.050	2.393	2.135	-0.064	-0.912
Routine task	4.340	2.235	4.268	2.251	0.072	0.946
Manual task	1.696	1.478	1.691	1.475	0.004	0.087
Unemployment rate	6.636	1.200	8.092	1.461	-1.456	-33.681
Signal	0.000	0.705	0.000	0.699	0.000	-0.000
N	3,330		1,172			

Table 2.6: Effects of UI on Post-Unemployment Wage Growth

	τ_b		τ_s	
	No controls (1)	Full controls (2)	No controls (3)	Full controls (4)
τ	0.031	0.041	0.0023	0.035
	(0.039)	(0.040)	(0.042)	(0.042)
Search durations (weeks)		-0.0005		-0.0004
		(0.002)		(0.002)
N	1,785	1,785	1,785	1,785

All specifications control for age and age squared. Full controls includes search durations (weeks), years of education, race dummy, and household net liquidity wealth (quartiles). τ_b and τ_s indicate the treatment status; an eligibility for tier 1 UI extensions. Standard errors clustered by state in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.7: Effects of UI on Post-Unemployment Occupational Changes

	τ_b		τ_s	
	No controls (1)	Full controls (2)	No controls (3)	Full controls (4)
τ	1.848**	1.150	1.949**	1.658**
	(0.776)	(0.773)	(0.832)	(0.825)
Search durations (weeks)		0.205***		0.206***
		(0.031)		(0.031)
N	1,785	1,785	1,785	1,785

All specifications control for age and age squared. Full controls includes search durations (weeks), years of education, race dummy, and household net liquidity wealth (quartiles). τ_b and τ_s indicate the treatment status; an eligibility for tier 1 UI extensions. Standard errors clustered by state in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.8: Difference in Differences in Occupational Distance by Treatment Status

	T	Control	Treatment	Difference
	0	10.805	11.405	0.600
		(15.190)	(15.552)	
τ_b	1	10.221	11.617	1.396
		(14.566)	(16.894)	
	DID			0.796
	0	10.861	11.315	0.454
		(15.270)	(15.358)	
τ_s	1	10.227	11.792	1.565
		(14.547)	(17.229)	
	DID			1.111

$T = 0$ indicates before EUC is implemented, and $T = 1$ indicates post-EUC periods. Standard deviations in parenthesis.

Table 2.9: Selection Equation

	Selection
n	-0.013***
	(0.002)
Search duration	-0.026***
	(0.001)
Age	0.038***
	(0.011)
Age squared	-0.001***
	(0.000)
Net liquidity	
Q2	-0.264***
	(0.057)
Q3	-0.087
	(0.058)
Q4	-0.087
	(0.059)
Abstract task	0.027**
	(0.012)
Routine task	0.005
	(0.009)
Manual task	0.006
	(0.015)
Constant	-0.322
	(0.296)
N	6,292

Quartiles for household net liquidity is used to measure liquid asset levels. Standard errors clustered by state in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.10: Difference in Differences Estimation

	(1)		(2)		(3)		(4)	
	τ_b	τ_s	τ_b	τ_s	τ_b	τ_s	τ_b	τ_s
Signal	-1.566***	-1.565***	-1.539***	-1.537***	-1.523 ***	-1.523***	-1.539***	-1.537***
	(0.297)	(0.297)	(0.280)	(0.280)	(0.276)	(0.276)	(0.278)	(0.278)
Net liquidity								
Q2	-0.637	-0.654	-1.698***	-1.703***	-1.676***	-1.681***	-1.660***	-1.672***
	(0.469)	(0.469)	(0.503)	(0.497)	(0.496)	(0.490)	(0.501)	(0.494)
Q3	1.134**	1.124***	0.800	0.796	0.805	0.802	0.801*	0.803
	(0.469)	(0.480)	(0.487)	(0.485)	(0.484)	(0.482)	(0.481)	(0.479)
Q4	1.625***	1.620***	1.150**	1.150***	1.175**	1.174**	1.176**	1.174**
	(0.527)	(0.525)	(0.529)	(0.529)	(0.538)	(0.537)	(0.531)	(0.529)
Age	-0.124***	-0.125***	-0.152***	-0.153***	-0.151***	-0.151***	-0.151***	-0.152***
	(0.024)	(0.024)	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)
τ	-0.033	-0.290	-0.529	-0.826	-0.520	-0.815	-0.521	-0.817
	(0.751)	(0.815)	(0.646)	(0.834)	(0.759)	(0.830)	(0.762)	(0.832)
T	-0.300	-0.387	-1.049***	-1.136***	-0.775	-0.861	-0.355	-0.358
	(0.468)	(0.458)	(0.482)	(0.468)	(0.625)	(0.604)	(0.641)	(0.647)
$\tau \times$ T	1.314**	1.856**	1.227**	1.766***	1.234*	1.781***	1.804**	2.991***
	(0.669)	(0.701)	(0.646)	(0.668)	(0.641)	(0.659)	(0.847)	(0.862)
Nonselection hazard			10.058***	10.053***	9.877***	9.866***	9.853***	9.812***
			(1.639)	(1.644)	(1.564)	(1.570)	(1.556)	(1.573)
p1					-1.219	-1.229	-1.984*	-2.161*
					(0.804)	(0.807)	(1.074)	(1.160)
p2					-0.123	-0.125	-1.500	-1.547
					(1.246)	(1.244)	(0.928)	(0.933)
p1 $\times$ EUC tier at p1							1.270	0.785
							(1.283)	(1.460)
p2 $\times$ EUC tier at p2							1.819	1.430
							(1.343)	(1.403)
p3 $\times$ EUC tier at p3							-2.170	-2.994**
							(1.306)	(1.390)
Constant	20.974***	20.862***	12.706***	12.789	12.637***	12.719***	13.102***	13.280***
	(3.817)	(3.819)	(3.615)	(3.619)	(3.613)	(3.617)	(3.647)	(3.657)
N	4,502	4,502	4,502	4,502	4,502	4,502	4,502	4,502

Table 2.11: Wage Regressions

	ln wage
Abstract task	0.050**
	(0.021)
Abstract task squared	0.005*
	(0.002)
Routine task	-0.026
	(0.025)
Routine task squared	0.008***
	(0.003)
Manual task	-0.024
	(0.033)
Manual task squared	0.010
	(0.006)
Age	0.125***
	(0.007)
Age squared	-0.001***
	(0.000)
Black	-0.177***
	(0.041)
Constant	3.120***
	(0.182)
N	4,502

Residuals from this equation is the productivity signal from the pre-unemployment occupations. The regression is controlled by year and state specific effects, and years of education. Standard errors clustered by state in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.12: Matching Estimation

	Nearest neighbor matching		Propensity score matching	
	(1)	(2)	(3)	(4)
	τ_b	τ_s	τ_b	τ_s
ATE	1.284*	1.333*	1.649**	1.855**
	(0.748)	(0.796)	(0.817)	(0.889)
N	2,403	2,403	2,403	2,403

Matching estimators for the average treatment effects on occupational changes between pre- and post-unemployment occupations. The number of match is 1. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.13: Assessing Unconfoundedness:
Estimates of Average Treatment Effects for Pseudo Outcomes

	Nearest neighbor matching		Propensity score matching	
	(1)	(2)	(3)	(4)
	τ_b	τ_s	τ_b	τ_s
ATE	-0.525	-0.383	-0.042	-0.042
	(0.815)	(0.881)	(0.814)	(0.875)
N	2,099	2,099	2,099	2,099

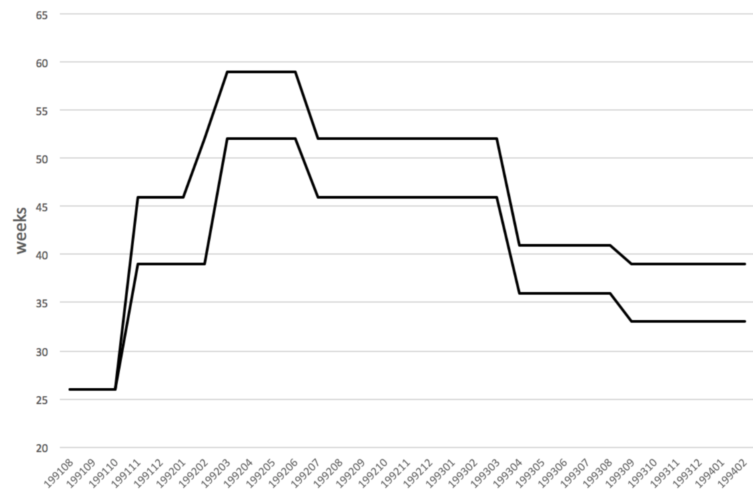
Matching estimators for the average treatment effects on the pseudo outcomes; occupational changes between pre- and post-unemployment occupations before the EUC is implemented. The number of match is 1.

Table 2.14: Relationship Between Search Durations and Occupational Changes

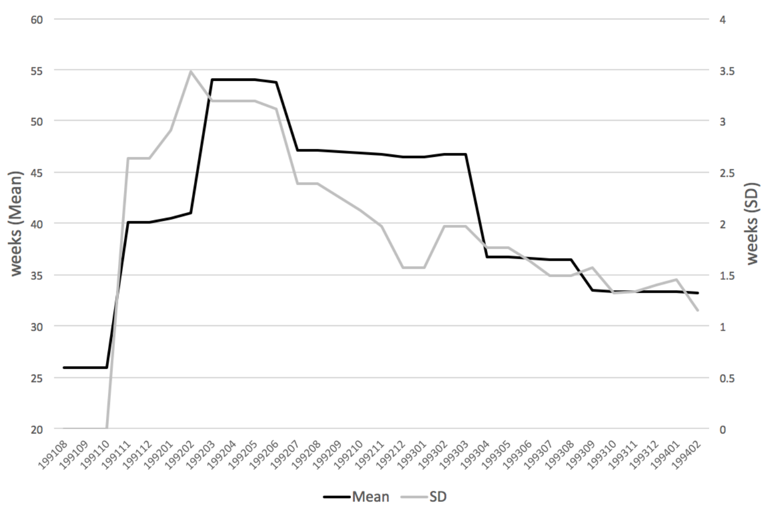
	Search durations (weeks)
Distance	0.114***
	(0.014)
ln wage	1.693***
	(0.454)
Signal	-2.075***
	(0.554)
Unemployment rate	0.767***
	(0.163)
Net liquidity	
Q2	0.753
	(0.563)
Q3	-0.130
	(0.511)
Q4	0.662
	(0.731)
Age	0.070***
	(0.020)
Education	-0.244**
	(0.075)
Black	4.358***
	(0.790)
Constant	-4.137
	(2.287)
N	4,502

Distance measures occupational changes between pre- and post-unemployment occupations. Quartiles for household net liquidity is used to measure liquid asset levels. Standard errors clustered by state in parentheses. The regression is controlled by year specific fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.1: Variation in Total Weeks of UI Benefits Available

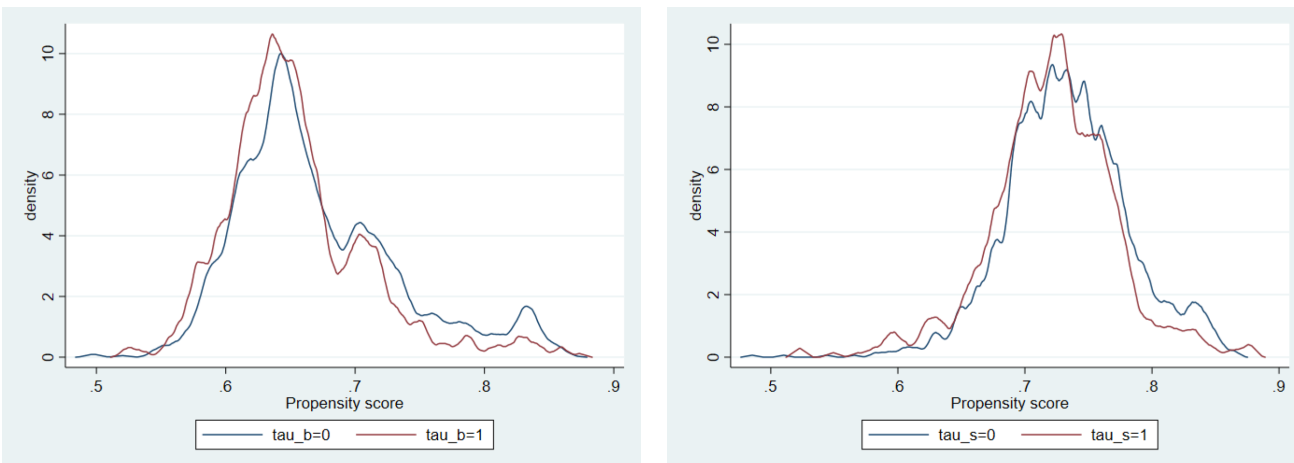


A. Maximum and Minimum Across States



B. Mean and Standard Deviation Across States

FIGURE 2.2: Propensity Score Overlap



Chapter 3

Employer Learning of Multi-Dimensional Ability

3.1 Introduction

Since the pioneering work by Farber and Gibbons (1996) that put Spence (1981) to empirical test, a sizable literature has now developed on testing the presence of the signaling value of education by exploring the presence of employer learning in the labor market. Owing to its simple setup and testable predictions, many variations of the model have now been developed and studied[1]. These models all assume that employers may use schooling attainment and other readily-observable characteristics to predict worker productivity and that employers might respond by resetting wages as the true productivity of their workers is revealed over the course of their careers. The model has two key predictions. One, the importance on wage of ability measures

[1] One such variation is used to test the existence of statistical discrimination in the labor market: see Altonji (2005); Altonji and Pierret (2001) for earlier works using the employer learning models.

that are correlated with productivity but not observed by employers should increase with experience, as firms learn about their workers' true productivity. Two, the importance on wage of readily observable measures, such as years of schooling or race, should decline with years of worker experience if such measures initially serve as signals of abilities.

In this paper, we ask whether the role of employer learning in the wage-setting process varies by the tasks being performed on the job. In doing so, we address how choice of occupation in a given period affects occupational mobility in the following period. The literature on employer learning has mostly been concerned with testing the presence of employer learning at a given level of educational attainment, but such an approach implicitly assumes that the rate of employer learning is independent of the type of job tasks. Studies that consider the role that job task plays with respect to the speed of employer learning have thus far lacked discussion of the endogeneity in occupational choices.

We build on a theoretical model of Altonji (2005), in which workers choose occupations based on their expectations about their own skills and in which each occupation reveals different amounts of information about their skills. We extend the model to allow multi-dimensional skills and tasks. The model predicts a three-way interaction term of skills, tasks, and experience to be positive, meaning that the effect of uncertain ability on wage growth increases with intensity of job tasks, because intensive job tasks reveal more information about workers' skill levels. The model also has implications for occupational choice: workers choose their occupations, given noisy information about their skill sets. Thus, the task intensity of a worker's job can be a determinant for occupational mobility over the lifecycle when productivity signals vary by task intensity.

We depart from the standard employer learning literature in interpreting different measures of skills as a noisy measure of ability. Typically, in the literature, true productivity is assumed to be composed of four additive parts: those observable to econometricians only, to firms only, to both econometricians and firms, and to neither. One of the difficulties in implementing the model lies in finding a measure that is observed only by econometricians: AFQT scores are almost always used as one such measure but without much defense. With our definition of ability, the noisiness of the skill measure initially observed by the firm and the skill measures used in the wage regression suggest the sign of key parameters in the model, while upholding the model's key implications. Rather than having to rely on assumptions about the observability of a skill measure to assign parameters a priori, our definition allows for inferring whether a measure of skill, or a proxy of it, is used in the wage setting process ex post.

To test the model implications in a multi-dimensional skill setting, we take a direct measure of task intensities for three-digit occupation groups. These measures are created by taking answers to relevant questions from the Occupational Information Network (O*NET), as used in earlier studies. By not relying on level of education, which is positively correlated with task intensities, the role of task type within any given educational group can still be tested.

For our main analysis, we use data from the National Longitudinal Survey of Youth 1979 (NLSY79). We focus on two task measures – abstract tasks and social tasks – and for three mutually exclusive educational groups – high school graduates, some college, and college graduates. We find that employer learning depends on the type of tasks in a given job, especially for cognitive skills, as well as that the degree of task-based employer learning varies across educational groups. In particular, our analyses show that for college graduates, cognitive tasks seem to play a key role in employer learning, while social tasks are more important for high school graduates.

One concern that arises in using current job task as an explanatory variable in a log wage equation is endogeneity. The decision to change jobs involves the arrival of information that is correlated with the worker's productivity. Hence, job switching may be positively correlated with a productivity shock. Due to this possible complication of job switching, the literature relies on estimating the presence of employer learning conditional on the first job only. We first address the endogeneity using means that are typically used elsewhere in the literature: controlling for the first job. We then turn to an instrumental variable approach, using the Markov property of Bayesian learning, where the previous periods' occupation is used as an instrument. We instrumentalize the first period's occupation using workers' occupational aspirations in 1982.

We build on a number of previous papers that study the importance of education's signaling value by testing the presence of employer learning or evaluating the evidence of statistical discrimination in wage structures (Farber and Gibbons (1996);

Altonji and Pierret (2001); Arcidiacono et al. (2010); Lang and Manove (2011); Mansour (2012); Kahn and Lange (2014); Light and McGee (2015)). Light and McGee (2015) brings the "importance of skills" measure from O*NET for each of the seven component scores in the Armed Services Vocational Aptitude Battery (ASVAB) in the NLSY79. Using the pre-market skills proxied by the ASVAB scores and the skill importance measures, Light and McGee (2015) estimates nonstructural parameters that are related to screening (an employer's ability to screen for skills before hiring) and learning for different types of workers (i.e., for high school and college graduates, and for blue- and white-collar workers), and for skills' differing types and levels of importance. They find that different skill types display distinct tradeoffs between learning and screening. However, they also find that the extent of employer learning does not vary significantly across skill type or worker type.

Our empirical analysis is closely related to the reduced-form analysis introduced in Light and McGee (2015), but we take a different approach in order to test the effect of task-intensity on the speed of employer learning. We exploit proxies for cognitive and social skills from the NLSY79 and corresponding task-intensity measures for the two skill types; these task-intensity measures are constructed by Autor and Dorn in Autor and Dorn (2013) and by Deming as used in Deming (2017). We find that task intensities are important factors in determining employer learning and wage progressions, and they have different impacts by worker type, namely for high school vs. college graduates.

3.2 Employer Learning Model with Occupation-Specific Job Task

We build on a theoretical model by Altonji (2005), which builds on a standard employer learning model (e.g., Farber and Gibbons (1996) and Altonji and Pierret (2001)), and we extend the framework to allow multi-dimensional skills and tasks.[2] We formally further the development of an idea previously developed in Light and McGee (2015), that one's productivity at different jobs that require different sets of skills reveals information about said worker's true skills at different rates. This is because the sensitivity of output to a given worker's skill should depend on how intensively that skill is used in the job: for example, performing a hypothetical job that requires no social skills should not reveal any information to an employer about the worker's true social skills. This is consistent with Sanders (2014) and Bahk (2020), who find that workers learn about their skills by changing to new jobs that require different combinations of tasks.

We assume, as in Farber and Gibbons (1996) and Altonji and Pierret (2001), that a worker and employers in the labor market have symmetric information about the worker i's true skill level $\mathbf{q}_i = (q_{1,i}, ..., q_{J,i})$ where q_j, $j = 1, ..., J$ denotes distinct skill-set, such as cognitive and social skills.[3] Therefore, all separations between workers

[2] There is fast-growing literature on human capital formation and development, highlighting the importance of multi-dimensional skills in determining various outcomes, including years of schooling and labor market productivity. See, for example, Heckman and Rubinstein (2001), Papageorge et al. (2019), Deming (2017), among many.

[3] The employer learning literature assumes symmetric information and also assumes that AFQT score is unobserved to employers in the market. This in turn implies that workers also do not

and firms and job mobilities are efficient and agreed upon by the agents. We make an additional assumption that $\mathbf{q}_i$ is time-invariant, i.e., there is no human capital accumulation over time and the evolution of wages entirely reflects leaning and changes in occupations. The productivity y, given a time-invariant vector of true skill levels, $\mathbf{T}$, and a vector of task intensities performed in a given job, $\mathbf{T}_{it} = (T_{1,i,t}, ..., T_{J,i,t})$ for an individual i at time t is:

$$y_{it} = \mu\mathbf{q}_i + \mathbf{T}_{it}A\mathbf{q}_i' - \mathbf{T}_{it}B\mathbf{T}_{it}'. \tag{3.1}$$

given an $1 \times J$ matrix $\mathbf{q}_i$ and $J \times J$ diagonal matrices A and B, which are parameters of the model. Given the assumption on matrices A and B, equation (3.1) can be written as:

$$y_{it} = \sum_{j=1}^{J}(\mu_j q_{j,i} + A_j T_{j,i,t} q_{j,i} - B_j T_{j,i,t}^2) \tag{3.2}$$

where A_j and B_j are $jj-th$ elements of matrices A and B, respectively. We assume $A_j > 0$ and $B_j > 0$ for all j. In the subsequent discussion, we will omit i subscripts. The first of these implies that workers who are more skilled at jth skill have a comparative advantage in jobs that require a higher intensity of that task compared to other workers. This is because the higher T_j is, the more sensitive y is to change in q_j. The latter assumption means that choosing jobs with more intensive tasks comes with higher productivity costs and the costs may differ for the two tasks. Lastly,

observe their own AFQT scores. Guvenen et al. (2020) defends this assumption by arguing that only a limited amount of information about AFQT scores is revealed to the test takers.

given the setup, y is independently determined by the two tasks and worker skill in each dimension.

We assume that agents observe skill-specific productivity signals g_{jt} for each skill j and each period $t = 1, 2, ..., n$. For example, agents learn how good a worker is at cognitive tasks and social tasks separately. The signal is determined by a worker's skill q and choice of occupation T, and the idiosyncratic noise ϵ. Thus, the amount of new information that the agents gain for each skill may vary depending on the task levels in each skill dimension.

$$g_{jt} = T_{jt}q_j + \epsilon_{jt}, \quad \epsilon_{jt} \sim N(0, \sigma^2_{\epsilon_j}), \tag{3.3}$$

Given a productivity signal g_{jt}, the mean and variance of an agent's belief about q_j at t can be written as

$$\begin{aligned} \hat{q}_{jt} &= E_t(q_j | g_{jt}, ..., g_{j1}, \hat{q}_{j0}) \\ &= \frac{\hat{q}_{j0}\sigma^2_{\epsilon_j} + \sum_{\tau=0}^{t} T_{j\tau} g_{j\tau} \sigma^2_{\eta j0}}{\sigma^2_{\epsilon_j} + \sum_{\tau=0}^{t} T^2_{\tau} \sigma^2_{\eta j0}} \end{aligned} \tag{3.4}$$

$$\begin{aligned} \sigma^2_{\eta jt} &= Var_t(q_j | g_{jt}, ..., g_{j1}, \hat{q}_{j0}) \\ &= \frac{\sigma^2_{\epsilon}\sigma^2_{\eta j0}}{\sigma^2_{\epsilon_j} + \sum_{\tau=0}^{t} T^2_{j\tau} \sigma^2_{\eta,0}} \end{aligned} \tag{3.5}$$

where $\hat{q}_{jt}$ represents agents' expectation about worker's jth skill, and $\sigma^2_{\eta jt}$ denotes the variance of agents' belief at time t.

Equation (3.3) implies that as task T_j increases, the signal provides more valuable information about a worker's skill q_j. Therefore, the learning speed depends on the relative information content of the agent's initial belief and on the new information gained through learning as shown in (3.4) and (3.5).

We assume the labor market is competitive. Firms infer workers' skill $\mathbf{q}$ and then pay according to workers' expected productivity each period. Workers choose an occupation, i.e., a vector of task levels $\mathbf{T}_t$, each period to maximize their expected lifetime wage, given their belief about their own skills. We may reach the simple solution by backward induction. In the final period n, w_n is

$$w_n = \max_{T_{jn}, j=1,\ldots,J} (\sum_{j=1}^{J} \mu_j \hat{q}_{jn} + A_j T_{jn} \hat{q}_{jn} - B_j T_{jn}^2) \tag{3.6}$$

The optimal task choice that satisfies the first-order condition is $T_{jn}^* = \frac{a}{2b} \hat{q}_n$. In the previous period, the worker maximizes the following wage function:

$$\begin{aligned} w_{n-1} &= \sum_{j=1}^{J} (\mu_j \hat{q}_{jn-1} + A_j T_{jn-1} \hat{q}_{jn-1} - B_j T_{jn-1}^2) + \mathbb{E}_{n-1}[\sum_{j=1}^{J} (\mu_j \hat{q}_{jn} + A_j T_{jn}^* \hat{q}_{jn} - B_j {T_{jn}^*}^2)] \\ &= \sum_{j=1}^{J} (\mu_j \hat{q}_{jn-1} + A_j T_{jn-1} \hat{q}_{jn-1} - B_j T_{jn-1}^2) + \mathbb{E}_{n-1}[\sum_{j=1}^{J} (\mu_j \hat{q}_{jn} + \frac{a^2}{4b} \hat{q}_{jn})] \\ &= \sum_{j=1}^{J} (\mu_j \hat{q}_{jn-1} + A_j T_{jn-1} \hat{q}_{jn-1} - B_j T_{jn-1}^2) + \sum_{j=1}^{J} (\mu_j \hat{q}_{jn-1} + \frac{a^2}{4b} \hat{q}_{jn-1}), \end{aligned} \tag{3.7}$$

because $\mathbb{E}_{n-1}(\hat{q}_{jn}) = \mathbb{E}_{n-1}(\mathbb{E}_n(q_j|g_{jn})) = \mathbb{E}_{n-1}(q_j) = \hat{q}_{jn-1}$. Therefore, $T^*_{jn-1} = \frac{a}{2b}\hat{q}_{jn-1}$ and similarly, $T^*_{jt} = \frac{a}{2b}\hat{q}_{jt}$ for all t.

Equations (3.4) and (3.5) imply that workers with low T learn more slowly due to noisier signals. Assuming that $var(\eta_0)$ and $var(\epsilon)$ are identical for different groups of people (for example, high school and college graduates), the group with the higher average task level will resolve skill uncertainty at a faster rate and experience lower levels of occupational mobility over their career. However, the model may have a mixed prediction about occupational mobility if the variances of initial belief or the pure (signal) noise varies for different groups of workers. Given that task intensities are fixed, the learning speed is slower when the variance of initial belief or of signal is higher.

The model implies that there are two channels through which task levels $\mathbf{T}$ affect wages. First, wage changes more sensitively according to worker skill at higher task levels because of its increasing sensitivity on outputs. The second effect is through learning; with higher $\mathbf{T}$, more information is revealed through more precise productivity signals. Therefore, wage growth is more heavily dependent on skills when workers have higher occupations.

3.2.1 Employer Learning Framework

Farber and Gibbons (1996) and subsequently Altonji and Pierret (2001) develop a framework to test for employer learning. One key assumption is that a worker's true productivity can be decomposed into four additive components. There are four types of measures of q_j: (i) observable to econometricians but not to the firm (z_j), (ii) observable to the firm but not to econometricians (h_j), (iii) observable to both parties (s_j), and (iv) observable to neither (e_j).[4] In particular, omitting j subscript, as the original models concern one dimensional skills, the true skill of a worker is written as

$$q = rs + \alpha h + \Gamma z + e. \tag{3.8}$$

and employers form expectations of factors they cannot observe (z, e), given the factors that they can observe (s, h). Econometricians, on the other hand, do not observe h, which firms use to construct expectations about a worker's productivity and have to infer about it using what they can observe: z. That is, the true wage generating process is: $w_t = \beta_0 + \beta_1 s + \beta_2 h + \hat{e}_t + \zeta_t$, where $\hat{e}_t$ is $\mathbb{E}_t(e|g_1, ..., g_t)$ and econometricians can only run regressions of the following form: $w_t = \gamma_0 + \gamma_1 s + \gamma_2 z + \nu_t$.

Since workers' wages depend on ability measures that econometricians do not observe, coefficients on z in wage regressions that econometricians run are misspecified. In particular, the regression suffers from omitted-variable bias. If employer learning occurs, there will be a time-varying component of the omitted-variable bias because employers use more information to form expectations and determine wages as time passes. The test of employer learning centers around this idea.

One of the difficulties in implementing the outlined test is to find measures that are unobserved by the employer, and to the workers under symmetric information

[4]The two papers differ in that Farber and Gibbons (1996) develops a method to test for employer learning, while Altonji and Pierret (2001) builds on that model to test for statistical discrimination.

assumption. Naturally, one criticism of this method is whether AFQT scores, which are widely used measure for z, are in fact unobserved. Further, equation (3.8) is also restrictive in assuming that the four components of q are related in a particular way.

Instead of following the conventional definition of q, we use lessons from the measurement error model [5] and assume that s, h, and z are all noisy measures of the true ability q. This setup keeps the intuition and strategy used in a standard employer learning model without having to search for a measure of z.

The following model illustrates the strategy to test employer learning and statistical discrimination under our definition of q. Let skill measures be:

$$h = q + \epsilon^h$$

$$z = q + \epsilon^z$$

where ϵ^h and ϵ^z are random noise, and assume that s is the same for everyone. Further assume that ϵ^h and ϵ^z are independent. In the first period, firms only observe h and pay:

$$w_1 = \delta_0^F + \delta_1^F h + \epsilon_1^F.$$

If employer learning occurs and ability q is fully revealed in Period 2, then wage in Period 2 is:

$$w_2 = \delta_0^F + \delta_1^F q + \epsilon_2^F.$$

[5] For an overview of the empirical application of measurement error models, see Hu (2017). Cunha et al. (2010)

Consider running the following regression in each period:

$$w_t = \delta_0^E + \delta_{1,t}^E z + \epsilon_t^E.$$

Then $\delta_{1,1}^E = \frac{\delta_1^F}{Var(\epsilon^h)+Var(\epsilon^z)}$, and $\delta_{1,2}^E = \frac{\delta_1^F}{Var(\epsilon^z)}$. Both estimates suffer from attenuation bias, but the magnitude of the bias changes across period due to the second-period reduction in noise about true skill. In the above case, bias moves away from 0. Similarly, if $z = h$ in the above example – that is, if the noise of the included variable is highly correlated with measures used by firms to set wages – we can get estimates that move toward 0 as t increases.

The implication of Altonji and Pierret (2001)model that years of schooling coefficient, (a measure that firms can easily observe) will decrease over time and the AFQT coefficient (a measure that firms do not observe) will increase over time when learning occurs. Formally, Altonji and Pierret (2001) propose the following regression model to test for employer learning and statistical discrimination:

$$w_{it} = \beta_0 + \beta_S S_i + \beta_{SZ} S_i X_{it} + \beta_{Z,t} Z_i + \beta_X X_{it} + \beta_{ZX} Z_i X_{it} + \epsilon_{it}, \tag{3.9}$$

where X_i indicates years of experience. A negative β_{SZ} means that firms initially used S_i, an observable characteristic that is a noisy measure of the true ability q, and thus indicates statistical discrimination based on S_i. Likewise, a positive β_{ZX} indicates that firms learn over time about workers' true ability.

Task-Dependent Employer Learning

Our goal is to test whether the role of employer learning in the wage-setting process varies by the intensity of the tasks being performed on the job. In order to test this, we augment equation (3.9) to include task intensity measures:

$$w_{it} = \beta_a S_i + \beta_2 Z_i + \beta_3 S_i \times X_{it} + \beta_4 Z_i \times X_{it} + \beta_5 Z_i \times T^Z_{it} + \beta_6 Z_i \times X_{it} \times T^Z_{it} + \epsilon_{it}. \quad (3.10)$$

The task-specific employer learning model in section 3.2 implies that $\beta_6 > 0$. If task-dependent learning occurs, high T increases the accuracy of the productivity signal of the worker's true ability q, therefore strengthening the relationship between Z and wage growth. In Altonji (2005), he makes a similar argument, where T is replaced with S. The reasoning behind his using S is that S is positively correlated with task intensity level, which leads to a greater flow of information, whereas we use the direct measure of task intensity T instead of S. We will discuss details of this model in section 3.3.2.

3.3 Empirical Evidence

We use the NLSY 79, widely used in the employer learning scholarship, to test the theoretical implications discussed in section 3.2. We first discuss the dataset used, then test for employer learning using an extension of the standard employer learning model discussed in section 3.2.1. We then explore the model prediction on choice of occupation and occupational mobility. In section 3.3.4, we discuss the endogeneity issue.

3.3.1 NLSY 79 Dataset

The data used in the study are drawn from the 1979–2004 waves of the NLSY79. We only use these earlier waves for two reasons. First, the use of the 1979–2004 waves is consistent with earlier studies, in particular Arcidiacono et al. (2010), which subsequent papers in statistical discrimination and employer learning often replicate. Second, we follow Arcidiacono et al. (2010) in restricting our attention to the part of the distribution where the relationship between log wages, AFQT, and potential experience are linear, which corresponds to experience levels less than 13 years.

The main analytic sample is thus restricted to 25,692 individual–year observations for whom the above-mentioned variables are observed. Our sample is identical to that of Arcidiacono et al. (2010), with the exception of our inclusion of the "some college" educational group.

The key variables used in this analysis are constructed as follows. We focus on two dimensions of abilities: cognitive and non-cognitive (social) skills, which are not observed by both employers and workers. To measure cognitive task intensity, we use the abstract task measure constructed by Autor and Dorn (2013) using the data from the Dictionary of Occupational Titles (DOT). The abstract task measure is the average of two DOT variables, "direction control and planning" and "GED Math," measuring managerial, mathematical, and formal reasoning requirements. We use the

AFQT score from the NLSY for the relevant cognitive skill measure for the abstract task. As in Arcidiacono et al. (2010), we use the standardized AFQT score for each age at which the test was taken. For social tasks, we take a measure constructed in Deming (2017) using the Occupational Information Network (O*NET) which is the successor of the DOT. The social task measure is the average of four O*NET variables: "coordination," "negotiation," "persuasion," and "social perceptiveness." Non-cognitive skill, then, is measured using the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale, which are also used by Heckman et al. (2006) and Deming (2017).

Table 3.1 summarizes the individuals who compose the analytic sample. Column (1) does so for the full sample, and Columns (2)–(4) do so separately for individuals' educational achievement. In most subsequent analyses, we report estimates separately for high school graduates and 4-year college graduates, following Arcidiacono et al. (2010), who showed that falsely aggregating the two groups could lead to bias in the estimates. Further, we include a 'some college' group, which consists of individuals who have enrolled in college but did not obtain a 4-year college degree. Our rationale for adding this group is the fact that about half of all students who enroll in college in the U.S. eventually drop out (Hotz et al. (2018)); given this group's size, the signaling value of the partial completion of college merits analysis. Our choice to include them is also due to recent research that explicitly notes that individuals with some college – but less than a four-year degree – have socioeconomic trajectories that closely resemble those of high school graduates (Lundberg et al. (2016)). If this is true, we should observe similar patterns of employer learning for high school graduates and for individuals with some college education.

Table 3.1 shows differences in initial cognitive ability as measured by AFQT and in job tasks denoted “Abstract” across the three educational groups. College graduates, compared to high school graduates, have AFQT scores that are about 1 standard deviation higher, and the average AFQT score of the “some college” group lies about halfway between the other groups. It is also noteworthy that both the social and the abstract task requirements at jobs increase with education, although the initial distribution of social scores across the three groups does not appear to vary. The table thus suggest that individuals with different educations work in occupations that require different sets of skills. In particular, those with more years of education, on average, work in occupations that have higher abstract and social task demands.

This feature in the data motivates our analysis. Given the predictions of our model, the higher task intensity observed for college graduates suggests that the slower learning with respect to high school graduates’ cognitive ability (something widely found in the literature) may partly result from high school graduates’ working in occupations that are less cognitive-skill-intensive and from the finding that, on average, college graduates have a comparative advantage with respect to social and abstract tasks. In this case, such a difference in learning may occur within an educational attainment group.

In Figure 3.1, we explore how average task intensities change with years of potential experience. The figure shows that average abstract and social task intensities increase with years of education and with years of potential experience. Consistent with Table 3.1, average task intensities for both abstract and social job contents are highest for those who hold bachelor's degrees and lowest for high school graduates. The job contents of the "some college" group lies between the other two educational attainment groups for all levels of potential experience and are statistically different from the contents of the other two groups. Figure 3.1 also shows that both the abstract and social contents in a given job increase with experience, on average.

The difference in the task intensities across these groups remains stable over time. Given the difference in the initial distribution of these skills, this stability has an important implication in addressing human capital accumulation. Namely, given the task skill measures, initial skill distribution, and choice of job tasks outlined in 3.2, this suggests that if human capital accumulation exists, the degree of learning does not depend much on years of schooling. This is an important insight because the employer learning model assumes that additional human capital is orthogonal to observed skill measures; hence we can attribute changes in coefficient over time to changes in firms' information set.

Figure 3.2 shows the relationship between initial skills and career progression in terms of job tasks, by plotting how the abstract contents of jobs change over time. The top-left panel of Figure 3.2 shows that people with higher AFQT scores work in jobs that have higher abstract contents from the start and that the difference in the task intensiveness grows over time. Interpreting this pattern in the context of the employer learning literature, the plot suggests both that employers are able to screen employees early on and that they also learn about their employees over time. Additionally, the relatively small movements in task intensity for the college graduates observed in Panel (d) and increasing task content in Panel (b) are consistent with previous findings of revelation of ability at the start of one's career for college graduates but not for high school graduates.

As our theoretical model predicts, the plots indeed suggest that occupational choice can also reveal employer learning, in addition to wage, the latter of which is primarily used in this strand of literature. Also, it highlights one important limitation of the employer learning model: the model cannot distinguish the effect of human capital accumulation from the effect of employer learning. Through most of this paper, we will use the term employer learning without distinguishing it from the idea of human capital accumulation. Separation of these two effects requires stronger assumptions in the form of human capital accumulation function and the method of learning, or additional data on ability measures. We do not address these.[6]

Figure 3.2 also reveals three empirical patterns. First, with the exception of the "some college" group, the highest type and the lowest type appear always to distinguish themselves from others: this is consistent with the theoretical results of Lang and Manove (2011). This finding also highlights the possibility that initial occupational choice can be used as a signaling channel, in addition to years of schooling. Moreover, it reveals a potential mechanism through which employer learning might

[6]Farber and Gibbons (1996) address this. find initial skill-human capital accumulation complementarity. The true results would be weaker than what we find.

occur; perhaps employer learning occurs through workers' repeated signaling efforts throughout their careers, whereby each worker exerts effort to signal productivity (Kaya (2009)). Second, the degree of employer learning appears to vary with the initial skill level, especially for high school graduates. Third, there appears to be considerable noise in the occupational choices of the "some college" group, but after 5 years, cognitive task intensity and AFQT score measures align.

Figure 3.2 shows that most of the changes in job contents occur among individuals in the middle of the education–AFQT distribution. The abstract task content of high school graduates in the lowest quintile does not change much over time, and the abstract task intensity stays relatively flat for college graduates in higher AFQT quintiles. By contrast, task intensities for other groups is generally shown to increase over time, a pattern that, in turn, contrasts with the implications of models of human capital investment that view jobs as a combination of different skills, as formalized in Cavounidis and Lang (2020). Under the model, people would overinvest in the skills that they use most intensively, meaning that we would observe steeper changes in task intensity within the intersection of the highest-quantile-AFQT and highest-education groups.

3.3.2 Testing Employer Learning Using Wage Regressions

We estimate the following equation to test for the presence of employer learning for the three different educational groups:

$$w_{it} = \beta_1^{S_i} + \beta_2^{S_i} Z_i + \beta_3^{S_i} X_{it} + \beta_4^{S_i} Z_i \times X_{it} + \beta_5^{S_i} Z_i \times T_{it}^Z + \beta_6^{S_i} Z_i \times X_{it} \times T_{it}^Z + \epsilon_{it} \quad (3.11)$$

where S_i is educational attainment, Z_i is a vector of skill measures that consists of AFQT scores and social scores[7], X_{it} is years of potential experience at time t, and T_{it}^Z is a vector representing job contents. We also include a vector of demographic controls that include region of residence, a binary indicator of urban residence, and race.

Assuming Z_i and T_{it}^Z to be scalars to fix ideas, the test of task-dependent employer learning constitutes testing $\beta_6 > 0$. The analysis in section 3.2 suggests that the effect of Z on wage growth increases with T^Z, due to an increase in information flow, with larger T^Z. If task-dependent learning occurs, a high Z increases T^Z, which makes the signal of the true ability q more accurate, thus strengthening the relationship between Z and w. This argument is similar to that made in Altonji (2005), if Z is replaced with S. In his model, the goal was to test the signaling value of education when firms differ in their production technology, whereas we are interested in testing the signaling value of job tasks in such a market.

[7]These skills would constitute skill measures unobserved to firms but observed to econometrician in a classic employer learning model, while such distinction is not needed under our framework.

The sign of the coefficient estimates of β_2, β_4 are also of interest. Following the assumption in the employer learning literature that Z_i contains part of the productivity-relevant characteristics that firms find harder to observe, a positive β_2 coefficient indicates that a portion of those characteristics are revealed at the time of labor market entrance. The coefficient on the interaction term of skills and experience, β_4, shows whether the importance of the hard-to-observe skill measure, Z_i changes over time. If Z_i affects productivity and if employer learning occurs, then we would expect the coefficient on β_4 to be positive. The magnitude of these coefficients, however, is not readily interpretable. As discussed in section 3.2, the test of employer learning relies on the change in the coefficients' bias over time.

The analysis in this section is most closely related to the analyses in Mansour (2012) and Light and McGee (2015), which study the role in employer learning of a worker's first job after the completion of education. Mansour (2012) investigates this by dividing the jobs using the Census 2-digit occupation code and analyzing the changes in residual variances across these occupations. Light and McGee (2015)'s approach is closer to our paper: they study the role of task intensities of the first job in revealing information about workers' true productivity. We differ in that we use the information of all CPS jobs. Furthermore, the two papers mentioned use the characteristics of the first job, due to endogeneity concerns associated with job-switching behavior. We will address this in section 3.3.4.

Table 3.2 presents OLS estimates of the regression model in equation (3.11). Columns (1)–(3) report coefficient estimates for the main analytic sample, Columns

(4)–(6) do so for white people in the sample, and Columns (7)–(9) do so for black people in the sample. Within each column, we report coefficient estimates separately for high school graduates, the "some college" group, and college graduates. For abstract task, comparison of the first two coefficients on Columns (1) and (3) shows a significant, positive coefficient for $AFQT$ for college graduates; a significant, positive coefficient on $AFQT \times T$ for high school graduates; and insignificant coefficients for the other two groups. This is consistent with results in Arcidiacono et al. (2010).

The estimate of β_6 of abstract task for college graduates is positive and significant, as theory suggests. The corresponding estimate for high school graduates is significant and negative, contrary to what theory suggests. One possibility is that high school graduates choose jobs wherein they hold a comparative advantage over college graduates, and from there they increase in the task content of these job, which tend to involve fewer cognitive tasks.[8]

The coefficients on "social task" are negative in all specifications in Columns (1)–(3). That type of task is valued more over time, as indicated by the positive coefficients of the interaction term $ST \times X$. One possibility is that some degree of complementarity and substitutability of abstract and social tasks, given firms' production technologies, drive this. The coefficients for social skill and its interaction with experience are insignificant both for high school graduates and for college graduates. The "some

[8]We suspect that the type of skill they choose is manual tasks; regression of wage on job tasks, including manual tasks, shows that the sign of the manual task coefficient is positive and significant for high school graduates and less so for college graduates. The opposite pattern holds for abstract tasks. We include "abstract task" and not "manual task" here because the NLSY lacks credible measures of manual skills.

college" group exhibits evidence of learning of cognitive skill and early revelation of social skills. Unlike for either of the other groups, the β_6 coefficients for both of the abilities – cognitive and social – remain insignificant.

Table 3.2 also supports the learning story for white and black college graduates, but the coefficient on $AFQT$ is significant only for black people. Given that the mean of abstract task intensity for college graduates is above 6, the estimates suggest that task-based learning occurs for white college graduates. For black college graduates, firms appear to learn about cognitive skill as proxied by the $AFQT$ test.

3.3.3 Choice of Occupation and Revelation of Ability

The literature on employer learning and statistical discrimination is largely silent on the choice of occupation and its role in the revelation of ability. The original model of employer learning considered a labor market wherein firms would have homogeneous technology and symmetric information. Much of the literature shares this assumption; however, Altonji (2005) and Mansour (2012) are two notable exceptions. The first considers the choice of occupation theoretically; the latter informally suggests that the choice of occupation may lead to differences in speed of learning across different occupations.

The model in section 3.2 predicts that the initial occupational choice, and each subsequent choice of occupation, can signal ability known to workers up to time t. Because the precision of the signal of ability is stronger when task intensity is high, changes in occupational task intensity are more strongly related to task intensity in the previous period and to the observed ability measure conditional on the experience.

Table 3.3 tests this prediction by observing how the distance of occupational tasks changes across periods ($|T_t - T_{t-1}|$). Column (1) shows that higher task intensity in the previous period is associated with a smaller change. This might arise because information about skills might be revealed early for people with very intensive jobs, and these individuals are not likely to move afterwards. The difference in occupational mobility by black people that appears in Column (1) is explained by difference in AFQT. Column (4) adds an interaction term of $AFQT$ and $AbstractTask$ to the specification. The results show that both of these variables separately explain task mobility. Repeating the analysis for each educational subgroup in Columns (5)–(7) is consistent with this. College graduates, who have the highest average level of AT are less likely to make job switches that would demand a large change in cognitive task intensity, while high school graduates and "some college" workers show more sizable changes.

3.3.4 Controlling For Endogeneity

Given that occupation at time t is a choice made by the worker, it is likely that the decision to change jobs involves the arrival of information that correlates with the productivity of the worker. This correlation could bias our coefficient estimate of β_6, as those who observe a high productivity shock for a particular occupation may choose that occupation.

We control for potential bias arising from this source of endogeneity using the previous period's task intensity as an instrument. The use of this instrument results from the assumptions set forth in the employer learning literature. Namely, the error term ϵ_{it} in (3.10) should be independent of information known at time $t-1$. Workers' task choices depend only on the current belief about skill, as discussed in section 3.2; thus, T_{it-1} is independent with ϵ_{it}. The results are shown in Table 3.4.

Consistent with earlier findings, we observe the presence of learning. The estimated change in the effect of $AFQT$ over time is positive, but this difference is statistically insignificant. Taken together, the evidence suggests that employer learning about cognitive ability occurs even for college graduates and that the speed of learning varies by job task. The estimates on social skills, on the other hand, suggest that social skill appeared to be fully revealed at the time of hiring and/or that social skills do not affect productivity.

3.4 Conclusion

In this paper, we question whether the role of employer learning in the evolution of wages varies according to the type of task(s) being performed on the job. To allow for multi-dimensional skills and tasks, we extend a theoretical model of Altonji (2005), in which each occupation reveals different amounts of information. While Altonji (2005) suggests employing workers' education level as a proxy for the difficulty of the job tasks they perform, we use direct measures of cognitive and social task intensities for three-digit occupational groups. We test the model prediction that the effect of uncertain ability on wage growth increases with task intensity because intensive job tasks reveal more information about workers' skill, and we find that employer learning depends on multi-dimensional tasks. In particular, we find that the effects of task intensities in learning vary by worker education level; for college graduates, cognitive tasks seem to play a key role in employer learning, while social tasks are more important for high school graduates. To address the endogeneity issue that arises when using the current job task as an explanatory variable, we show consistent findings from exploiting the previous periods' occupation and occupational aspiration as an instrument.

Table 3.1: Summary Statistics By Education

	(1) All	(2) HS Grad	(3) Some College	(4) 4-Yr Degree
Skill and Job Task measures				
AFQT	0.20	-0.08	0.41	1.04
	(1.00)	(0.93)	(0.81)	(0.59)
Social Score	0.40	0.39	0.41	0.43
Job Task: Social	4.25	3.29	4.47	6.69
	(2.74)	(2.33)	(2.64)	(2.22)
Job Task: Abstract	2.73	1.88	2.75	4.97
	(2.32)	(1.64)	(2.20)	(2.44)
SES and Demographics				
Log of Real Wage	6.77	6.65	6.78	7.14
	(0.50)	(0.43)	(0.47)	(0.50)
black	0.28	0.32	0.31	0.17
Year of Birth	1960.68	1960.85	1960.42	1960.26
	(2.21)	(2.14)	(2.23)	(2.33)
Education				
Years of Education	13.20	12.00	13.78	16.64
	(2.28)	(0.00)	(0.73)	(1.13)
HS	0.46	1.00	0.00	0.00
Come College	0.20	0.00	1.00	0.00
4-Year Degree or More	0.23	0.00	0.00	1.00
Region of Residence				
Northeast	0.19	0.19	0.17	0.22
North Central	0.28	0.29	0.25	0.29
South	0.39	0.39	0.39	0.34
West	0.14	0.13	0.19	0.15
Urban Residence	0.78	0.74	0.81	0.87
Potential Experience				
Potential Experience	6.47	6.61	6.59	6.14
	(3.31)	(3.30)	(3.30)	(3.29)
Ages < 25	3.35	3.50	2.94	1.56
	(1.76)	(1.66)	(1.55)	(0.91)
Ages 25-30	7.21	8.35	6.95	4.47
	(2.51)	(1.69)	(2.25)	(2.02)
Ages 30-35	9.82	11.29	10.15	8.61
	(2.24)	(1.34)	(1.99)	(2.18)
Ages > 35	10.11	7.69	9.57	10.44
	(2.44)	(2.98)	(3.03)	(2.10)
Actual Experience				
Actual Experience	5.62	5.90	5.41	4.79
	(3.30)	(3.33)	(3.17)	(3.19)
Ages < 25	2.65	2.80	1.88	0.51
	(1.84)	(1.74)	(1.32)	(0.58)
Ages 25-30	6.49	7.60	5.61	3.39
	(2.49)	(1.72)	(1.97)	(1.62)
Ages 30-35	9.30	10.67	9.08	7.86
	(2.07)	(1.41)	(1.84)	(1.80)
Ages > 35	9.55	7.56	9.20	10.15
	(2.58)	(3.13)	(3.14)	(1.80)
Observations	25692	11796	5090	5966

Notes: This table presents means of variables where individual-year observations are the unit of analysis. Standard deviations for non-binary variables are reported in parenthesis. HS denotes high school. Job tasks are on a 0-10 scale.

TABLE 3.2: OLS–Employer Learning

	All			Whites			Blacks		
	(1) HS	(2) SC	(3) C	(4) HS	(5) SC	(6) C	(7) HS	(8) SC	(9) C
AFQT	0.005	-0.017	0.102***	0.005	-0.026	0.078*	0.004	-0.001	0.103*
	(0.013)	(0.032)	(0.036)	(0.017)	(0.039)	(0.045)	(0.022)	(0.054)	(0.060)
AFQT × X	0.013***	0.007*	-0.011	0.013***	0.006	-0.007	0.014***	0.007	-0.022**
	(0.002)	(0.004)	(0.007)	(0.003)	(0.005)	(0.010)	(0.004)	(0.008)	(0.010)
Abstract Task (AT)	0.055***	0.066***	0.042***	0.058***	0.076***	0.040***	0.043***	0.030	0.065***
	(0.009)	(0.011)	(0.008)	(0.010)	(0.013)	(0.009)	(0.016)	(0.019)	(0.019)
AFQT × AT × X	-0.001**	-0.000	0.003***	-0.002**	0.001	0.003*	-0.001	-0.001	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Social Skill (SS)	0.010	0.058***	0.026	0.009	0.051**	0.032	0.019	0.110***	-0.013
	(0.010)	(0.021)	(0.021)	(0.012)	(0.024)	(0.023)	(0.021)	(0.042)	(0.043)
SS × X	-0.001	-0.003	0.002	-0.001	-0.004	0.002	-0.000	-0.003	-0.001
	(0.002)	(0.004)	(0.006)	(0.002)	(0.005)	(0.007)	(0.003)	(0.008)	(0.015)
Social Task (ST)	-0.049***	-0.029***	-0.009	-0.056***	-0.034***	-0.011	-0.028***	-0.015	-0.010
	(0.006)	(0.009)	(0.009)	(0.007)	(0.012)	(0.010)	(0.010)	(0.016)	(0.018)
ST × X	0.003***	0.003**	0.004**	0.003***	0.004***	0.005***	0.002	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)
SS × ST × X	0.001**	0.000	-0.000	0.001**	0.001	-0.000	0.000	0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
N	11225	4808	3835	7689	3256	3133	3536	1552	702

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log wage. Parentheses contain standard errors that are robust to clustering at the individual level. All specification control for urban residence, a cubic in experience, full-time status and year fixed effects.

TABLE 3.3: Occupational Mobility – Difference in Tasks

	Spec 1	Spec 2	Spec 3	Spec 4			
	(1)	(2)	(3)	(4) All	(5) HS	(6) SC	(7) C
Abstract Task (AT)							
AT_{t-1}	-0.360***		-0.381***	-0.423***	-0.505***	-0.528***	-0.598***
	(0.004)		(0.005)	(0.005)	(0.008)	(0.012)	(0.012)
Black	-0.371***	-0.053*	-0.190***	-0.204***	-0.220***	-0.306***	-0.139
	(0.027)	(0.032)	(0.029)	(0.028)	(0.039)	(0.071)	(0.086)
AFQT		0.008	0.184***	-0.110***	-0.045**	-0.344***	-1.268***
		(0.011)	(0.011)	(0.014)	(0.019)	(0.043)	(0.068)
AFQT $\times$ AT_{t-1}				0.015***	0.012***	0.025***	0.051***
				(0.000)	(0.001)	(0.001)	(0.001)
Social Task (ST)							
ST_{t-1}	-0.374***		-0.374***	-0.383***	-0.469***	-0.470***	-0.522***
	(0.005)		(0.005)	(0.005)	(0.008)	(0.012)	(0.014)
Black	-0.326***	-0.069*	-0.317***	-0.299***	-0.217***	-0.348***	0.116
	(0.033)	(0.036)	(0.033)	(0.033)	(0.050)	(0.082)	(0.084)
Social Skill (SS)		0.004	0.087***	-0.191***	0.002	-0.456***	-1.852***
		(0.012)	(0.012)	(0.022)	(0.031)	(0.061)	(0.093)
SS $\times$ ST_{t-1}				0.064***	0.006	0.109***	0.281***
				(0.004)	(0.008)	(0.012)	(0.013)
N	20006	20006	20006	20006	7891	3418	2747

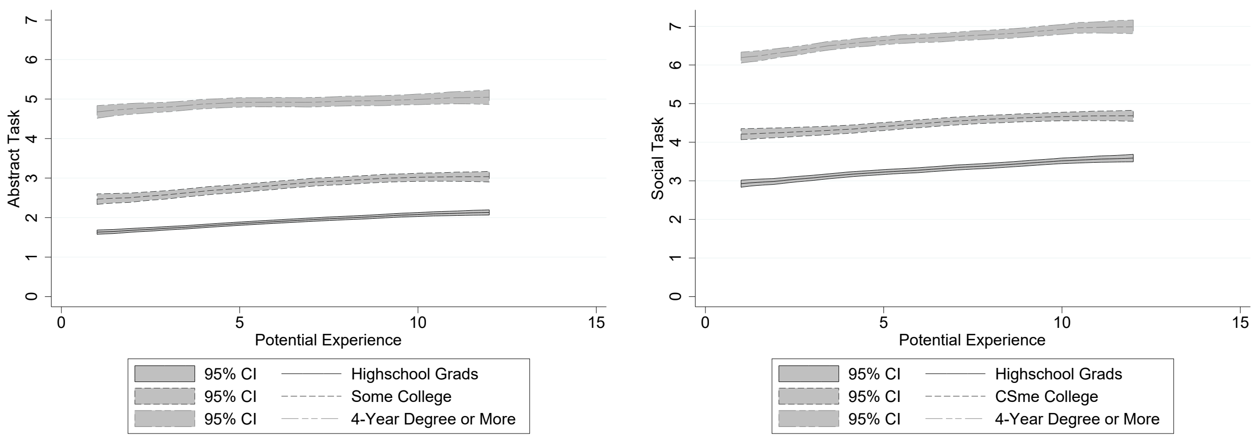
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is $|\text{Task}_t - \text{Task}_{t-1}|$. Parentheses contain standard errors. All specification control for a cubic in experience.

TABLE 3.4: IV–Employer Learning

	All			Whites			Blacks		
	(1) HS	(2) SC	(3) C	(4) HS	(5) SC	(6) C	(7) HS	(8) SC	(9) C
AFQT	-0.003	-0.046	0.074*	-0.004	-0.039	0.049	-0.005	-0.036	0.046
	(0.017)	(0.041)	(0.045)	(0.021)	(0.046)	(0.058)	(0.027)	(0.071)	(0.083)
AFQT × X	0.016***	0.007	-0.019**	0.016***	0.001	-0.014	0.016**	0.008	-0.026**
	(0.003)	(0.006)	(0.009)	(0.004)	(0.008)	(0.016)	(0.007)	(0.011)	(0.013)
Abstract Task (AT)	0.141***	0.203***	0.101***	0.134***	0.205***	0.104***	0.109	0.156	0.127**
	(0.036)	(0.039)	(0.023)	(0.039)	(0.042)	(0.026)	(0.105)	(0.098)	(0.052)
AT × X	-0.001	-0.013***	-0.005	0.000	-0.016***	-0.005	0.000	-0.005	-0.004
	(0.004)	(0.005)	(0.003)	(0.005)	(0.005)	(0.004)	(0.011)	(0.012)	(0.006)
AFQT × AT × X	-0.003***	0.000	0.004***	-0.003**	0.002	0.004	-0.003	-0.001	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)
Social Skill (SS)	0.012	0.060**	0.032	0.014	0.051*	0.050*	0.005	0.104**	-0.052
	(0.013)	(0.026)	(0.027)	(0.015)	(0.029)	(0.030)	(0.024)	(0.049)	(0.047)
SS × X	-0.002	-0.002	0.016	-0.003	-0.001	0.018	0.002	-0.015	-0.003
	(0.003)	(0.009)	(0.013)	(0.004)	(0.010)	(0.015)	(0.006)	(0.020)	(0.026)
Social Task (ST)	-0.123***	-0.095***	-0.107***	-0.121***	-0.081**	-0.139***	-0.108***	-0.130*	-0.050
	(0.018)	(0.031)	(0.039)	(0.021)	(0.034)	(0.044)	(0.037)	(0.068)	(0.073)
ST × X	0.005**	0.006*	0.010**	0.004	0.005	0.015***	0.005	0.008	-0.003
	(0.002)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)	(0.004)	(0.008)	(0.008)
SS × ST × X	0.001	0.000	-0.002	0.001	-0.000	-0.003	0.000	0.004	0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.005)	(0.004)
N	9536	4207	3474	6563	2864	2827	2973	1343	647

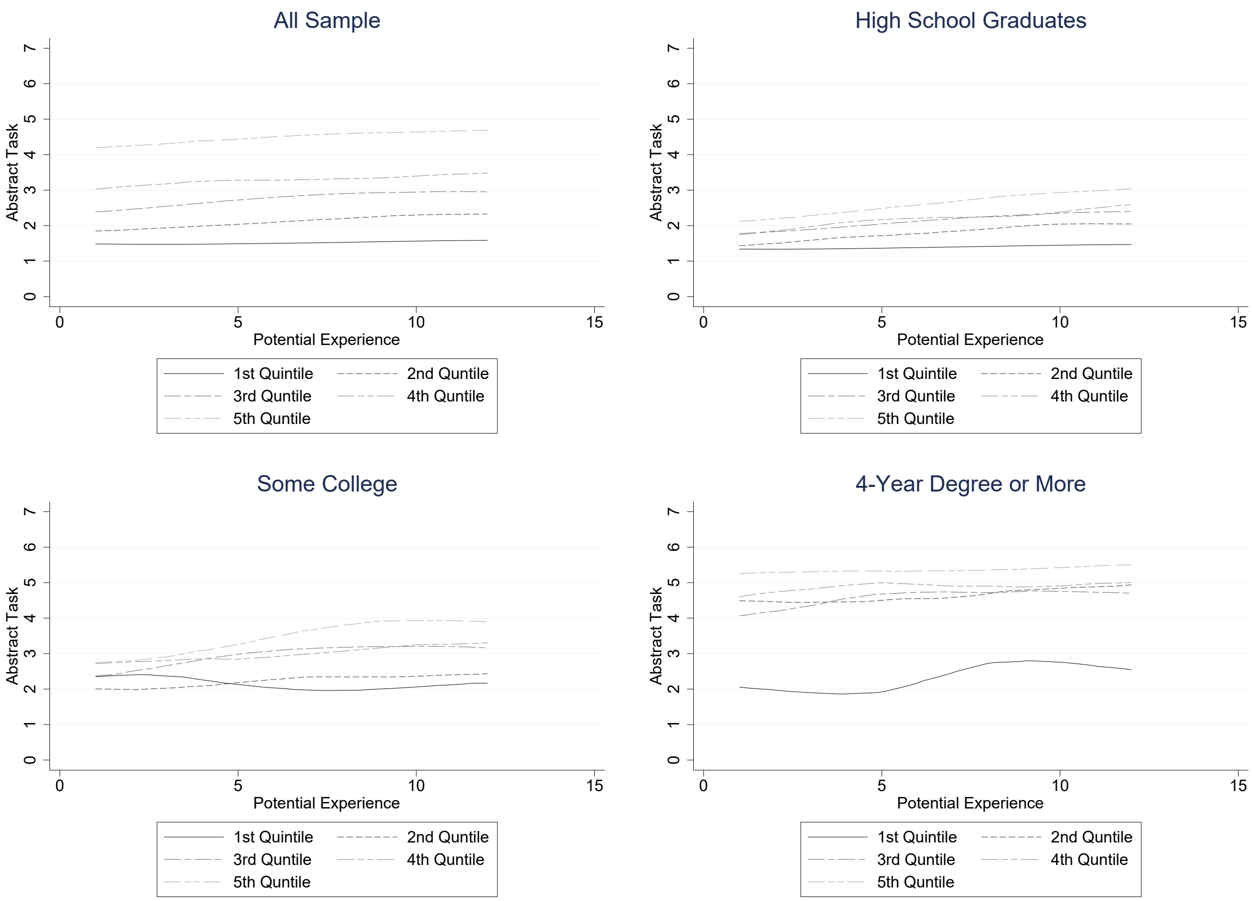
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log wage. Parentheses contain standard errors that are robust to clustering at the individual level. All specification control for urban residence, a cubic in experience, full-time status and year fixed effects.

FIGURE 3.1: Job Tasks by Potential Experience



Panel 3.1 plots conditional means of abstract task intensities by potential experience along with 95% confidence band. Panel 3.1 plots conditional means of social task intensities by potential experience.

FIGURE 3.2: Job Tasks and Potential Experience, by Education and AFQT Quintile



Panel 3.2 plots conditional means of abstract task intensities by potential experience by AFQT quintile of the analytic sample. Panel 3.2 does so for high school graduates. Panel 3.2 and Panel 3.2 do so for some college and college graduates, respectively.

Bibliography

Abadie, Alberto and Guido W Imbens, "Simple and bias-corrected matching estimators for average treatment effects," Technical Report, National Bureau of Economic Research 2002.

Addison, John T and McKinley L Blackburn, "The effects of unemployment insurance on postunemployment earnings," *Labour economics*, 2000, *7* (1), 21–53.

Althauser, Robert P and Donald Rubin, "The computerized construction of a matched sample," *American Journal of Sociology*, 1970, *76* (2), 325–346.

Altonji, Joseph G, "Employer learning, statistical discrimination and occupational attainment," *American Economic Review*, 2005, *95* (2), 112–117.

_ **and Charles R Pierret**, "Employer learning and statistical discrimination," *The Quarterly Journal of Economics*, 2001, *116* (1), 313–350.

Antonovics, Kate and Limor Golan, "Experimentation and job choice," *Journal of Labor Economics*, 2012, *30* (2), 333–366.

Arcidiacono, Peter, Esteban Aucejo, Arnaud Maurel, and Tyler Ransom, "College attrition and the dynamics of information revelation," Technical Report, National Bureau of Economic Research 2016.

_ **, Patrick Bayer, and Aurel Hizmo**, "Beyond signaling and human capital: Education and the revelation of ability," *American Economic Journal: Applied Economics*, 2010, *2* (4), 76–104.

Autor, David H and David Dorn, "The growth of low-skill service jobs and the polarization of the US labor market," *American Economic Review*, 2013, *103* (5), 1553–97.

_ **, Frank Levy, and Richard J Murnane**, "The skill content of recent technological change: An empirical exploration," *The Quarterly journal of economics*, 2003, *118* (4), 1279–1333.

Bacolod, Marigee, Bernardo S Blum, and William C Strange, "Skills in the city," *Journal of Urban Economics*, 2009, *65* (2), 136–153.

Bacolod, Marigee P and Bernardo S Blum, "Two sides of the same coin us residual inequality and the gender gap," *Journal of Human resources*, 2010, *45* (1), 197–242.

Bahk, Sung Ah, "Distributional Effects of Ability Learning and Career Choice," Technical Report, Working paper 2020.

Beffy, Magali, Denis Fougere, and Arnaud Maurel, "Choosing the field of study in postsecondary education: Do expected earnings matter?," *Review of Economics and Statistics*, 2012, *94* (1), 334–347.

Browning, Martin and Thomas F Crossley, "Unemployment insurance benefit levels and consumption changes," *Journal of public Economics*, 2001, *80* (1), 1–23.

Broyden, Charles G, "A class of methods for solving nonlinear simultaneous equations," *Mathematics of computation*, 1965, *19* (92), 577–593.

Cagetti, Marco, "Wealth accumulation over the life cycle and precautionary savings," *Journal of Business & Economic Statistics*, 2003, *21* (3), 339–353.

Card, David and Phillip B Levine, "Extended benefits and the duration of UI spells: evidence from the New Jersey extended benefit program," *Journal of Public economics*, 2000, *78* (1-2), 107–138.

_ **, Raj Chetty, and Andrea Weber**, "Cash-on-hand and competing models of intertemporal behavior: New evidence from the labor market," *The Quarterly journal of economics*, 2007, *122* (4), 1511–1560.

Carroll, Christopher D, "The method of endogenous gridpoints for solving dynamic stochastic optimization problems," *Economics letters*, 2006, *91* (3), 312–320.

Cavounidis, Costas and Kevin Lang, "Ben-Porath Meets Lazear: Microfoundations for Dynamic Skill Formation," *Journal of Political Economy*, 2020, *128* (4), 1405–1435.

Chetty, Raj, "Moral hazard versus liquidity and optimal unemployment insurance," *Journal of political Economy*, 2008, *116* (2), 173–234.

Classen, Kathleen P, "The effect of unemployment insurance on the duration of unemployment and subsequent earnings," *Industrial and Labor relations review*, 1977, pp. 438–444.

Cunha, Flavio, James J Heckman, and Susanne M Schennach, "Estimating the technology of cognitive and noncognitive skill formation," *Econometrica*, 2010, *78* (3), 883–931.

Deming, David J, "The growing importance of social skills in the labor market," *The Quarterly Journal of Economics*, 2017, *132* (4), 1593–1640.

Ehrenberg, Ronald G and Ronald L Oaxaca, "Unemployment insurance, duration of unemployment, and subsequent wage gain," *The American Economic Review*, 1976, *66* (5), 754–766.

Farber, Henry S and Robert Gibbons, "Learning and wage dynamics," *The Quarterly Journal of Economics*, 1996, *111* (4), 1007–1047.

Friedberg, Leora, "The labor supply effects of the social security earnings test," *Review of Economics and Statistics*, 2000, *82* (1), 48–63.

Gorry, Aspen, Devon Gorry, and Nicholas Trachter, "Learning and Life Cycle Patterns of Occupational Transitions," *International Economic Review*, 2019, *60* (2), 905–937.

Gourieroux, Christian, Alain Monfort, and Eric Renault, "Indirect inference," *Journal of applied econometrics*, 1993, *8* (S1), S85–S118.

Gourinchas, Pierre-Olivier and Jonathan A Parker, "Consumption over the life cycle," *Econometrica*, 2002, *70* (1), 47–89.

Gruber, Jonathan, "The Consumption Smoothing Benefits of Unemployment Insurance," *The American Economic Review*, 1997, *87* (1), 192–205.

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer, "Multidimensional skill mismatch," *American Economic Journal: Macroeconomics*, 2020, *12* (1), 210–44.

Heckman, James J, "Sample selection bias as a specification error," *Econometrica: Journal of the econometric society*, 1979, pp. 153–161.

_ **and Guilherme Sedlacek**, "Heterogeneity, aggregation, and market wage functions: an empirical model of self-selection in the labor market," *Journal of political Economy*, 1985, *93* (6), 1077–1125.

_ **and Yona Rubinstein**, "The importance of noncognitive skills: Lessons from the GED testing program," *American Economic Review*, 2001, *91* (2), 145–149.

_ **, Hidehiko Ichimura, and Petra Todd**, "Matching as an econometric evaluation estimator," *The review of economic studies*, 1998, *65* (2), 261–294.

_ **, Jora Stixrud, and Sergio Urzua**, "The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior," *Journal of Labor economics*, 2006, *24* (3), 411–482.

Hirano, Keisuke, Guido W Imbens, and Geert Ridder, "Efficient estimation of average treatment effects using the estimated propensity score," *Econometrica*, 2003, *71* (4), 1161–1189.

Hotz, V Joseph, Emily E Wiemers, Joshua Rasmussen, and Kate Maxwell Koegel, "The role of parental wealth and income in financing children's college attendance and its consequences," Technical Report, National Bureau of Economic Research 2018.

Hu, Yingyao, "The econometrics of unobservables: Applications of measurement error models in empirical industrial organization and labor economics," *Journal of econometrics*, 2017, *200* (2), 154–168.

Ingram, Beth F and George R Neumann, "The returns to skill," *Labour economics*, 2006, *13* (1), 35–59.

Johnson, Matthew and Michael P Keane, “A dynamic equilibrium model of the US wage structure, 1968–1996,” *Journal of Labor Economics*, 2013, *31* (1), 1–49.

Jovanovic, Boyan, “Job matching and the theory of turnover,” *Journal of political economy*, 1979, *87* (5, Part 1), 972–990.

_ **and Robert Moffitt**, “An estimate of a sectoral model of labor mobility,” *Journal of Political Economy*, 1990, *98* (4), 827–852.

Kahn, Lisa B and Fabian Lange, “Employer learning, productivity, and the earnings distribution: Evidence from performance measures,” *The Review of Economic Studies*, 2014, *81* (4), 1575–1613.

Kambourov, Gueorgui and Iourii Manovskii, “Occupational specificity of human capital,” *International Economic Review*, 2009, *50* (1), 63–115.

Kaya, Ayça, “Repeated signaling games,” *Games and Economic Behavior*, 2009, *66* (2), 841–854.

Keane, Michael P and Kenneth I Wolpin, “The career decisions of young men,” *Journal of political Economy*, 1997, *105* (3), 473–522.

Kimball, Miles S, “Precautionary Saving in the Small and in the Large,” Technical Report, National Bureau of Economic Research 1989.

King, Allan G, “Occupational choice, risk aversion, and wealth,” *ILR Review*, 1974, *27* (4), 586–596.

Kroft, Kory and Matthew J Notowidigdo, "Should unemployment insurance vary with the unemployment rate? Theory and evidence," *The Review of Economic Studies*, 2016, *83* (3), 1092–1124.

Krueger, Alan B and Bruce D Meyer, "Labor supply effects of social insurance," *Handbook of public economics*, 2002, *4*, 2327–2392.

Lalive, Rafael, "Unemployment benefits, unemployment duration, and post-unemployment jobs: A regression discontinuity approach," *American Economic Review*, 2007, *97* (2), 108–112.

Lang, Kevin and Michael Manove, "Education and labor market discrimination," *American Economic Review*, 2011, *101* (4), 1467–96.

Lee, Donghoon and Kenneth I Wolpin, "Intersectoral labor mobility and the growth of the service sector," *Econometrica*, 2006, *74* (1), 1–46.

Light, Audrey and Andrew McGee, "Employer learning and the importance of skills," *Journal of Human Resources*, 2015, *50* (1), 72–107.

Lundberg, Shelly, Robert A Pollak, and Jenna Stearns, "Family inequality: Diverging patterns in marriage, cohabitation, and childbearing," *Journal of Economic Perspectives*, 2016, *30* (2), 79–102.

MaCurdy, Thomas, David Green, and Harry Paarsch, "Assessing empirical approaches for analyzing taxes and labor supply," *Journal of Human resources*, 1990, pp. 415–490.

Mansour, Hani, "Does employer learning vary by occupation?," *Journal of Labor Economics*, 2012, *30* (2), 415–444.

Moffitt, Robert, "Unemployment insurance and the distribution of unemployment spells," *Journal of econometrics*, 1985, *28* (1), 85–101.

Neal, Derek, "The complexity of job mobility among young men," *Journal of Labor Economics*, 1999, *17* (2), 237–261.

Ours, Jan C Van and Milan Vodopivec, "Does reducing unemployment insurance generosity reduce job match quality?," *Journal of Public Economics*, 2008, *92* (3-4), 684–695.

Papageorge, Nicholas W, Victor Ronda, and Yu Zheng, "The economic value of breaking bad: Misbehavior, schooling and the labor market," Technical Report, National Bureau of Economic Research 2019.

Papageorgiou, Theodore, "Learning your comparative advantages," *Review of Economic Studies*, 2014, *81* (3), 1263–1295.

Pratt, John W, "Risk aversion in the small and in the large," in "Uncertainty in economics," Elsevier, 1978, pp. 59–79.

Rosenbaum, Paul R and Donald B Rubin, "Reducing bias in observational studies using subclassification on the propensity score," *Journal of the American statistical Association*, 1984, *79* (387), 516–524.

Roy, Andrew Donald, "Some thoughts on the distribution of earnings," *Oxford economic papers*, 1951, *3* (2), 135–146.

Rubin, Donald B, "Matching to remove bias in observational studies," *Biometrics*, 1973, pp. 159–183.

_ , "Formal mode of statistical inference for causal effects," *Journal of statistical planning and inference*, 1990, *25* (3), 279–292.

Sanders, Carl, "Skill accumulation, skill uncertainty, and occupational choice," Technical Report, Working paper 2014.

Spence, Michael, "Signaling, screening, and information," in "Studies in labor markets," University of Chicago Press, 1981, pp. 319–358.

Sullivan, Paul, "A dynamic analysis of educational attainment, occupational choices, and job search," *International Economic Review*, 2010, *51* (1), 289–317.

Topel, Robert H and Michael P Ward, "Job mobility and the careers of young men," *The Quarterly Journal of Economics*, 1992, *107* (2), 439–479.

Wiswall, Matthew and Basit Zafar, "Preference for the workplace, human capital, and gender," Technical Report, National Bureau of Economic Research 2016.

Yamaguchi, Shintaro, "Tasks and heterogeneous human capital," *Journal of Labor Economics*, 2012, *30* (1), 1–53.

Vita

Sung Ah Bahk was born in Seoul on November 6, 1988 and graduated summa cum laude with a Bachelor's degree in Economics from Ewha Womans University in 2012. She enrolled in the Economics PhD program at Johns Hopkins University in 2014. During her six years in graduate school, she was awarded the Joel Dean Undergraduate Teaching Award for Carl Christ Dissertation Award. In August 2020, she will join as an Assistant Professor at American University.